Social Media and Online Public Deliberation: A Case Study of Climate Change Communication on Twitter

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May 2022

A thesis submitted for the degree of Doctor of Philosophy of
The Australian National University

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

Yuanyuan Shang

May 2022

Acknowledgements

The PhD journey is hard, but it is fortunate that I enjoyed it, at almost every moment. I am privileged to take this opportunity to express my appreciation for the efforts, trust, respect and consideration of the people mentioned in this section.

First and foremost, I am enormously grateful to my supervisors, Professor Joan Leach, Associate Professor Will Grant and Professor Robert Ackland. Without their continuous support and guidance, this thesis would not have been possible. The continuous encouragement, constructive advice, timely feedback and valuable patience offered by my supervisory panel have not only guided my study but also taught me how to be a good researcher and a positive person. In particular, I would like to thank Joan, who showed me how well women can do in academia; I would like to thank Will, who taught me how to be positive in life; and I would like to thank Rob, whose constructive criticism helped me to improve my analytical thinking and skills.

I have been very fortunate to have had so many supportive and smart fellow students and colleagues at the Australian National University, especially at the Australian National Centre for the Public Awareness of Science. I am grateful to all the ‘Gardeners of CPAS’. Thank you, Mita, Nic, Emily, Karina, Hannah, Samantha and Matt. Thanks to Bea Hogan, our great manager of CPAS, the best administrator that I have ever met. She has always been very kind and helpful. Even just saying hello to her in the morning was enjoyable in the busy study life. Thanks to Merryn for offering me tutoring opportunities, even twice. I learned a lot when marking students’ assignments. I am also grateful to Nic, who accompanied me a lot through regular walks, rides, runs and talks, and made my life in Canberra much more interesting, especially during the pandemic. Thanks to my Chinese friends at ANU, Qiong, Jing, Huanyu, Xiaolan and Tong, hangouts with whom eliminated my homesickness.

I would like to thank my boyfriend, Xiaodong, who has been in the Netherlands pursuing his PhD degree. Years of long-distance relationship is in many ways hard, but we have become more independent and learned how to spend time and deal with troubles by ourselves, which is important.

This PhD experience has been particularly special because of the bushfire, hailstones and COVID-19. All the conferences and international programmes I attended in the first two years of my PhD have become more impressive and unforgettable. I am also very lucky to have got a job in the UK during the pandemic, for which I am also deeply grateful to my supervisory panel’s help, and the help from Professor Usic Kim, my advisor in the master’s program in Ewha Womans University, South Korea.

My candidature would have not been possible without the financial support provided by the Chinese Scholarship Council Scholarship, and the supplementary scholarship offered by the Climate Change Institute of the Australian National University.

Last but not least, I want to thank my parents and my elder brother, who have been incredibly supportive of me throughout this endeavour.

Abstract

This thesis studies the deliberative potential of social media, focusing on climate change communication on Twitter. In particular, this study seeks to explore the online deliberation seen in users' interactions and user-generated content from the perspectives of social network analysis and framing. Three research questions will be answered by three case studies focusing on climate change and an emerging technological topic related to climate change (negative emissions, intentional human efforts to remove CO_2 emissions from the atmosphere): how did the climate strikes impact the deliberative potential of climate change discussions online, how did users collectively frame climate change via hashtags, and how did different user groups on Twitter collectively frame negative emissions via tweets? Together, these three questions allow the construction of a picture on the overarching research question: what is the potential of online discussions for deliberation? The data was collected using Twitter's application programming interfaces, covering, for the general topic of climate change, the period 10 September 2018 to 10 September 2019 and, for the subtopic of negative emissions, the period 10 June 2019 to 10 September 2019.

There are three main findings of this thesis. First, it shows the changes of deliberative potential of climate change discussions before and after climate strikes and provides evidence that climate strikes increased the potential for deliberation by increasing reciprocity and diversity within the discussion of climate change. However, discussion of climate change after the climate strikes appears to have had less deliberative equality.

Second, the thesis reveals that users collectively frame climate change by selecting and associating different hashtags in tweets. In particular, users utilise different hashtags to serve different framing purposes. For example, they use hashtags about consequences, causes and solutions of climate change to spread meaning throughout the entire hashtag occurrence network. Users also tend to connect less popular hashtags with more popular hashtags and make the latter even more popular, and tend to connect hashtags in the same category together in general. The thesis also characterises how climate change is framed on Twitter. In particular, it shows evidence that users tend to frame climate change as a problem that we can solve, and highlights the need for further action.

Third, the thesis provides insights into negative emissions as an emerging technological topic, perhaps not as studied from a communication and social impact perspective as is warranted. The frames identified by structural topic modelling show various concerns of different user

groups, such as governments, the media and business, and give us clues to the current situation of the communication and acceptance of negative emissions.

As it focuses on the politics of climate change in the English language, the findings can not be generalised to all situations. However, it provides a research framework based on social network analysis and framing to examine the deliberative potential of online discussions and contribute to the understanding of climate change communication practice. This thesis provides a basis for future research that is expected to measure online deliberation more comprehensively and thoroughly, and improve our understanding of how social media is used by publics to communally work through the issues of climate change.

List of Abbreviations

ANU	The Australian National University
API	Application Programming Interfaces
ASCII	American Standard Code for Information Interchange
BECCS	Bioenergy with Carbon Capture and Storage
BLM	Black Lives Matter
CCS	Carbon Capture and Storage
CO2	Carbon Dioxide
COP	Conference of the Parties (of the UNFCCC)
COP24	The 24th UNFCCC COP
ERGMs	Exponential Random Graph Models
HPV	Human Papillomavirus
ICAS	Intelligent Cyber Argumentation System
IPCC	Intergovernmental Panel on Climate Change
LDA	Latent Dirichlet Allocation
LHS	Left Hand Side
MST	Minimum Spanning Tree
NGOs	Non-governmental Organizations
RHS	Right Hand Side
RQ	Research Question
SR15	The IPCC Special Report Global Warming of 1.5°C
STM	Structural Topic Modelling
UNFCCC	United Nations Framework Convention on Climate Change
URL	Uniform Resource Locator
VBA	Visual Basic for Applications

Glossary

Term	Definition
Degree	The total number of links that are connected to a node.
Density	The proportion of the total number of edges to the number of possible edges in a network.
Diameter	The longest distance between any pair of nodes, which represents the linear size of the network.
Discussion analysis	The attempt to directly measure aspects of deliberation by systematically examining the communication on Twitter around political issues.
Everyday political talk	Nonpurposive, informal, casual, and spontaneous political conversation voluntarily carried out by citizens, without being constrained by formal procedural rules and predetermined agenda.
Framing	A strategic action whereby individuals select some aspects of issues and make them more salient in communication.
Gini coefficient	The normalised expected difference in degree between two randomly selected nodes.
In-degree	The number of links that point inward at a node.
Mini-publics	A class of institutions that directly engage citizens, promote democratic deliberation and have, at times, been institutionalised into contemporary decision-making processes.
Negative emissions	The process of removing CO_2 emissions from the atmosphere by intentional human efforts.
Online deliberation	The informal online discursive process in which participants express their opinions and discuss with each other with the potential goal of achieving mutual and collective understanding about political issues.
Out-degree	The number of links that point outward from a node.
Reciprocity	The likelihood of vertices in a directed network to be mutually linked.
Social media	Internet-based channels that allow users to opportunistically interact and selectively self-present, either in real time or asynchronously, with both broad and narrow audiences who derive value from user-generated content and the perception of interaction with others.
Social movements	Loose networks of organisations and individuals with common values participating in politics using unconventional forms to reach political goals.
Spanning tree	A collection of connected links that include all nodes in the network, but that do not form a cycle.

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Chapter 1 Introduction

The last 30 years have seen the boom of the Internet, with a range of different opinions on the democratic potential of the digital space. On one side sit the 'cyber-optimists' (Davis, 1999), who welcome and applaud the positive effects of the Internet; for example, greater engagement in political issues can be encouraged by the lack of temporal and geographical restrictions online. On the other side sit the 'cyber-pessimists' (Janssen and Kies, 2005), who point to the worrying side effects that the Internet has brought to society, such as endangering the commitment and respect required for deliberation. At the same time, others in this camp such as Rosenberg (2005) point to the practical difficulty of meaningful deliberation on a widespread scale including ordinary citizens. There are, of course, many pieces of evidence in this debate and various ways of looking at it. But one way we can delve deeper in this question is to look at deliberation, a key moment in modern democracies, and the deliberative potential of online discourses. Examining the deliberative potential of online discourses can help us to understand the cyber optimism/pessimism debate. I argue in this thesis that social media brings the possibility to engage non-elites in deliberation, especially in complicated political issues such as climate change. In particular, I will examine the potential of deliberation on the key social media platform Twitter, and focus on the political issue of climate change, where that deliberation is suggested to be required, specifically through users' interaction and user-generated content.

1.1 Background

In early 2000s, the emergence and rapid diffusion of social media brought significant changes to the media ecosystem and the way that publics participate in political communication, for example, through personalised information sharing (Bennett and Segerberg, 2012), and organising collective political actions (Rheingold, 2000). These changes raised researchers' attention to the potential for social media to contribute to democracy (e.g. Rheingold, 2000; Halpern and Gibbs, 2013).

As one of the core components of democracy, deliberation has been gaining increasing research interest. Adapted from Dryzek (2000), Mansbridge (2015) suggested that we can define deliberation minimally and broadly as 'mutual communication that involves weighing and reflecting on preferences, values and interests regarding matters of common concern'. Online deliberation is defined in this thesis as **the informal online discursive process in which participants express their opinions and discuss with each other with the potential goal of achieving mutual and collective understanding about political issues**. With this definition, we can expand by exploring what occurs during deliberation, and what is necessary to enable it. Scholars such as Dryzek and Niemeyer (2010) have pointed out that, apart from institutionalised electoral procedures, society-wide communication and the corresponding bottom-up input are also crucial in deliberation. Many scholars have emphasised the critical role in deliberation of talk, the behaviour through which people share information or express opinions or feelings, in solving political conflicts and problems (Mansbridge et al., 2012). The role of talk in deliberation will be covered more in the literature review.

With the emergence and increased importance of social media and the recognised value of informal discursive processes for deliberation, it is crucial to study the nature of online deliberation on social media. Many studies have found that the deliberation emerging online is complex (Papacharissi, 2010). However, regardless of the extensively increased theoretical importance and empirical impact of deliberation, there is a lack of practical measurements of deliberation needed ‘to achieve valid and empirically meaningful results’ (Fleuß et al., 2018, p. 11), let alone for online deliberation.

Several scholars have examined the discussion networks on social media from the perspective of deliberation. For example, González-Bailón et al. (2010) analysed discussion threads from the Slashdot forum, a discussion forum founded in 1997, and found that online political discussion networks have a tendency to be broader and deeper than discussion networks on other topics, such as games and books. Shapiro and Park (2018) tested the deliberation potential in the discussion networks that follow the most popular climate change-related videos on YouTube, and found that elites undermine the deliberative potential of climate change discussions. Kwak et al. (2010) pointed out that Twitter as a medium for political deliberation facilitates political discussion among users. Besides examining the structure of discussion networks, other actors have also studied content that users generate, which is also valuable for us to explore deliberation on Twitter. Several studies have adopted hashtags as frame markers (e.g. Meraz and Papacharissi, 2013; Papacharissi and de Fatima Oliveira, 2012) to help, as they argue, eliminate researchers’ subjectivity in frame detection (Shi et al., 2020). Analysing hashtag co-occurrence networks helps to identify the relative prominence of individual hashtags and the strategies taken by users to frame the political issue (Wang et al., 2016). Furthermore, Converse (2006) suggested that citizens may organise their political thinking around what he called ‘visible social groupings’ (e.g. Christians wearing crosses) (p. 38) to simplify the ways to comprehend complicated political issues. This shows the importance of different user groups’ framing in deliberation. All these examples show that, though there is a lack of consistent measurements of online deliberation, scholars have found some evidence on the deliberative potential of online discussions and raised some possible approaches to conduct the examination. Specifically, in this thesis, deliberative potential means the extent to which an online discussion approximates the ideal of deliberation.

We can also consider deliberation from particular topics. In this thesis, I am going to narrow the study of online deliberation by looking at the problem of climate change.

1.2 The research problem

Climate change has been described as a ‘super wicked’ problem by scholars such as Levin et al. (2012) and Kahane (2018), because it is hard to solve with traditional responses that need defined problems, determined outcomes and designed solutions. On top of that, climate change has additional troublesome features, for example running out of time; causes and solutions being provided by the same objects; and non-existent or weak central authority that can solve the problem. Deliberation has been proposed by some scholars as a means of solving the climate change issue. For example, according to Warren (1996), deliberation promises a political environment within which the plurality of environmental values can be effectively and sensitively assessed and considered in decision-making.

Apart from climate change as a broad topic, communication about some emerging technologies related to climate change, such as negative emissions, has recently gained researchers’ attention. Negative emissions is the process of drawing down CO_2 (carbon dioxide) from the atmosphere, and the adoption of this kind of strategy has been identified as a potential pathway to climate change mitigation (Fuss et al., 2014; Minx et al., 2017). Although there are also nature-based means via which CO_2 is removed (such as processes in the oceans and on land), this thesis follows Minx et al. (2018) and defines negative emissions as ‘intentional human efforts to remove CO2 emissions from the atmosphere’ (p. 3). Some scholars, such as Buck (2016), Minx et al. (2017) and Colvin et al. (2019), have pointed out that, while the development of technological solutions is needed, how these possible solutions interact with social factors – such as acceptance and public attitudes – need to be understood.

With this background, I will focus on the deliberative potential of discussions on Twitter regarding climate change communication.

As introduced in Section 1.1, if we are to understand (and potentially improve) the potential for deliberation online, practical measurements of deliberation are needed. The informal discourses that reflect bottom-up input are important for studying deliberation. What’s more, it is critically important to understand the deliberative potential of the discussions on Twitter, especially for climate change communication.

Much research has focused on offline deliberation, such as face-to-face ‘mini-publics’ (e.g. Fishkin and Luskin, 2005), institutions that involve citizens directly to promote democratic deliberation (Grönlund et al., 2014), political institutions (e.g. Nanz and Steffek, 2005) or other offline settings (e.g. Ferree, 2002). However, less is known about the nature of deliberation online. There is a dearth of research that assesses the deliberative potential of the Internet and social media, such as on the topic of climate change (Cagle and Herndl, 2019), let alone testing it statistically and structurally. More specifically, the existing research (explored in greater detail in Chapter 4, Section 4.2.2 Measurements of deliberative potential) is inadequate for defining and measuring online deliberation.

Most of the present research about climate change communication has explored the coverage in mass media, especially newspapers. Apart from this dominant camp focusing on mass media, a number of studies have started to focus on the issue of climate change on social media (e.g. Koteyko et al., 2015; Newman, 2016; Fownes et al., 2018), and some studies have focused on certain groups of users on Twitter climate change communication specifically, such as organisations (Segerberg and Bennett, 2011) and scientists (Walter et al., 2019). But how other user groups are communicating climate change on social media and how they frame climate change differently over time are less known. Moreover, less is known regarding how we can understand framing via hashtags as a moment of deliberation.

1.3 Research aims and questions

A consistent definition and corresponding operationalisation of measurements of online deliberation is missing in the current scholarship. A closer exploration of the deliberation on social media related to climate change is also required in climate change research. Taking climate change as a case study, this research aims to provide fresh insights into the online deliberation from user-generated content and users’ interactions on Twitter. It also helps further comprehend the features of the communicative practices in the digital space. The key overall research question of the thesis is: what is the potential of online discussions for deliberation? To answer this question, I will first explore the measurements of online deliberation, and then focus on users’ collective sense-making of climate change.

Specifically, I seek to answer the following research questions in this thesis.

RQ1. How did the climate strikes impact the deliberative potential of climate change discussions online?

RQ2. How did users collectively frame climate change via hashtags?

This question will be answered in Chapter 5 by answering the three subquestions below. I manually categorise the hashtags based on the meanings, and measure the roles and connections of hashtags by analysing hashtag co-occurrence networks.

RQ2a. What kinds of hashtag have been selected on the topic of climate change on Twitter?

RQ2b. What hashtags played important roles in the framing process?

RQ2c. How did users associate hashtags related to climate change on Twitter?

RQ3. How did different user groups on Twitter collectively frame negative emissions via tweets?

This question will be answered in Chapter 6 by answering the following two subquestions. I will manually categorise the user groups and apply structural topic modelling to analyse the frames.

RQ3a. Who is talking about negative emissions on Twitter?

RQ3b. How did different user groups collectively frame negative emissions from 10 June to 10 September 2019?

1.4 Significance and scope

Focusing on the politics of climate change as discussed in English of climate change, this study looks at online discussions of climate change and a related emerging technology (i.e. negative emissions) with the Twitter dataset covering the period 10 September 2018 to 10 September 2019 and the period 10 June to 10 September 2019, respectively. This study will help address the current shortage of research in online deliberation and climate change communication and provide methodological and empirical measures. It will contribute to the body of knowledge in this area in two main aspects.

On one hand, it will contribute to methodological development by employing a research framework based on social network analysis and framing, utilising a range of techniques, such as hashtag co-occurrence network analysis, exponential random graph models and structural topic modelling and benefiting from a rich dataset. Specifically, first, it will contribute to building a framework for measuring online deliberation and operationalise the measurements in a structural approach. Exploring the discussion networks constructed by reply relationships can reveal users' interactions on Twitter. Second, the way I analyse hashtags using network analysis will provide an example for researchers who intend to know different roles of hashtags in framing and provide evidence that hashtags can be used as frame makers. Third, the minimum spanning tree I will apply to filter the hashtag co-occurrence networks will provide a method for researchers who struggle with making the visualisation of these networks easy to read. Fourth, the exponential random graph modelling I apply in Chapter 5 (See Section 5.3.2.3 Exponential random graph models and Section 5.4.5 ERGM) will show other researchers in climate change communication a possible way to test hypotheses related to the network formation process. Last but not least, it will show the possibility of combining quantitative and qualitative, structural and content-based, static and dynamic methods in the same study, which can compensate for the shortcomings of using a one-sided single method.

On the other hand, the findings in this thesis will contribute to climate change communication practices. They will provide evidence of the impacts of social movements on online deliberation, which can encourage more people and organisations to initiate social movements. It will also help to reveal how users on Twitter collectively frame climate change, which can fill the gap in the scholarship that mainly concerns celebrities, specialists or media presses. What's more, it will contribute to exploring and understanding the acceptance and public attitudes towards negative emissions, and to considering the social impacts of technologies of negative emissions. It is also helpful for communicators to choose the right communication strategy by proving evidence about the status of communication of negative emissions among the public.

1.5 Thesis structure

In Chapter 1, I have introduced the context of the study, identified the research objectives and questions, and argued the value of such research. I have also discussed the limitations of this study.

In Chapter 2, the existing literature will be reviewed to identify both what is known and gaps in the research on online deliberation, the deliberative potential of Twitter through discussion networks and collective framing, and online deliberation and climate change communication. The research questions will also be clearly stated.

In Chapter 3, the methodological framework will be presented. The adoption of a combination of a structure-based and a content-based approach will be justified, including applying network analysis and structural topic modelling in different cases studies. The challenge of big data collection will be reviewed, and the approaches that I took to collect Twitter data will also be introduced.

From Chapter 4 to Chapter 6, I will explore the online deliberation of climate change from three case studies. The detailed research designs will also be presented.

In Chapter 4, I will focus on the impacts on the deliberative potential of climate change discussions on Twitter brought by the social movement climate strikes, by using network analysis to analyse the structure of discussion networks. In Chapter 5, I will explore users' collective framing of climate change via hashtag co-occurrence networks, by investigating the frame amplification and frame articulation processes. In Chapter 6, I will look into different user groups' collective framing of negative emissions in tweets, using structural topic modelling.

In Chapter 7, I will summarise the whole thesis by reviewing the research purposes, summarising the findings and contributions of each case study, stating the limitations of this study, discussing the implications, recommending what can be done for future research. A conclusion of the thesis will also be given.

Chapter 2 Literature Review

2.1 Introduction

Modern politics is riven by complicated polarisation and difficult to solve problems. Many have spoken about deliberation as being a key pathway to solve some of these problems. For example, it has been argued that more deliberative public engagement techniques are required to break down rooted camps and to achieve common goals in the complex climate change issue (Hulme, 2009). Deliberation is defined by Wright and Street (2007) as 'a specific form of participation: informed discussion between individuals about issues which concern them, leading to some form of consensus and collective decision' (p. 850). While many studies of deliberation have focused on formal governance-oriented processes, processes of discussion, consideration, and thoughts that happen in everyday life and in online communication are also forms of deliberation. These informal processes are worthy of examination, which is the focus of this thesis. In this thesis, after reviewing others' definitions of deliberation, I define online deliberation as **the informal online discursive process in which participants express their opinions and discuss with each other with the potential goal of achieving mutual and collective understanding about political issues**.

Deliberation is essential to effective democracy for multiple reasons (Sartori, 1987). For example, individuals are treated as the best representatives of their experiences and interests, and the process of deliberation can promote shared meanings in articulating different kinds of experiences (Warren, 1996). People can propose actions that are beneficial for long-term decision-making via identifying both common and divergent interests in deliberation. According to Dryzek (2000), '[t]he essence of democracy itself is now widely taken to be deliberation, as opposed to voting, interest aggregation, constitutional rights, or even self-government'. However, scholars such as Rosenberg (2005) doubt the practical possibility of meaningful deliberation on a widespread scale including ordinary citizens. I argue in this thesis that social media brings the possibility to engage ordinary people in deliberation, especially for complicated political issues such as climate change.

Historical developments in media forms have had a significant impact on the way individuals participate in political issues, which in turn has influenced deliberation. For example, in the mass media era before social media came in the late 1990s, the general public mainly received information passively from the media, such as television, radio or newspapers, with limited channels available to express their own opinions. In this few-to-many dynamic, the content being broadcast or propagated would be filtered and selected by professional ‘gatekeepers’ at multiple levels, such as editors, reporters and advertisers. The audience can discuss with others but this is mainly limited to who they know, such as family members or friends, and it is difficult for them to have their opinions heard by the wider public. In such a way, how the general public knows and learns about societal issues is highly dependent on how the media and the gatekeepers frame the issues. In the late 1990s, the emergence and rapid diffusion of social media brought significant changes to the media ecosystem. Social media is defined as ‘Internet-based channels that allow users to opportunistically interact and selectively self-present, either in real time or asynchronously, with both broad and narrow audiences who derive value from user-generated content and the perception of interaction with others’ (Carr and Hayes, 2015, p. 50). On social media, the general public can generate content that can be broadcast to others, and communicate with others directly, even with elites, about political issues. As argued by Bennett and Segerberg (2012), these networked platforms (social media) afford new ways of citizen engagement in political issues through personalised information sharing. Featured by user-generated content, the emergence of social media created a new data source for exploring political discussions (Ince et al., 2017). While we know these new technologies have afforded a range of new modes of political interaction, the question of what these changes brought to the nature and possibility of deliberation via social media remains open.

The debate about the deliberative potential of social media – and, indeed, the Internet more broadly – can be summarised via two different camps. On the one side sit the cyber-optimists, who welcome and applaud the positive effects of the Internet, and on the other side sit cyber-pessimists, who argue for the worrying side effects that the Internet has brought to society. I argue that deliberation is the key element of this debate, and we can reframe this debate within the light of specific questions of deliberation. More precisely, can deliberation be achieved with new online forms of communication? Cyber-optimists argue that online forms of communication afford a bump in deliberative opportunities, whereas the cyber-pessimists suggest the constrains of social media are likely to reduce opportunities for deliberation. I argue that further evidence can be brought to this question. In particular, can the positive effects of deliberation be achieved via new online forms of communication? As typical platforms for new online forms of communication, social media is the focus of this thesis. I focus as a case study on the widely discussed political issue climate change on Twitter. A range of studies have attempted to measure how deliberative or democratic the online forums are. For example, Schneider (1997) measured the degrees to which the discussions on Usenet (newsgroups) satisfy the conditions of democratic theory. However, before examining how deliberative it is, I argue that we should focus on social media's potential for better deliberation by looking into the features of how users interact with each other and the content they generate.

Some scholars have worked on examining the deliberative potential of social media and its implication for climate change. For example, González-Bailón et al. (2010) emphasised the deliberative potential of online discussion networks, and Collins and Nerlich (2015) examined the deliberative potential of users' comment threads on articles about climate change, highlighting the discussion networks as 'key to overcoming polarisation and engaging various publics with the complex issue of climate change' (p. 189). Their studies have impacted my study in various ways.

This chapter outlines the literature that has informed my questions, methods, and data interpretation across the thesis. First, I review the study about deliberation, which leads to the discussion of the deliberative potential of social media. I then focus on Twitter and the deliberative potential in the discussion of climate change on Twitter. Each chapter also includes a discussion of literature relevant to that specific chapter.

2.2 Deliberation

Democracy is a term with both scholarly and wide popular usage. However, many different definitions exist. Different definitions of democracy have different focuses. Anckar (1982) categorised the definitions of democracy into two camps: the 'process definitions', which focus on the process that political decisions are made, and the 'content definitions', which focus on the content of decisions. A 'classical' definition of democracy is the institutional arrangement for people to decide issues by electing individuals to carry out their will and realise the common good (as summarised by Schumpeter, 1976). Schumpeter (1976) criticised this definition because of its lack of meaningful reference to the institutions' ability to afford the realisation of a 'general will', and instead defined democracy as 'the institutional arrangement for arriving at political decisions in which individuals acquire the power to decide by means of a competitive struggle for the people's vote' (p. 269), which has been widely used by American social scientists (Schmitter and Karl, 1991).

In many understandings of democracy, the deliberative system is one of the core components of democracy. The deliberative system refers to 'a talk-based approach to political conflict and problem-solving through arguing, demonstrating, expressing, and persuading' (Mansbridge et al., 2012, pp. 4–5). A typical example of deliberation is when the general public is engaged to determine local budget allocations. According to Barabas (2004), deliberation has two goals: consensus and enlightenment. Consensus means that ‘participants are supposed to aim for mutual understanding while casting their personal interests aside’ (p. 687). When discussing local budget allocations, people have different preferences and priorities as to who and what should get more money, but through conversations they come to a common decision while reserving part of their own preferences. Enlightenment, in this sense, entails deliberation improving knowledge, ‘so that participants come not only to a consensus, but also to an enlightened view concerning the problem at hand’ (p. 688). For example, after the conversations, besides the decisions they made, people get to know more about the status of different sectors that need more money and how urgent their situations are.

Deliberation has been positively valued by political theorists for different reasons. For example, compared to the unchallenged authority (e.g. institutions or experts) involved in decision-making, in which judgements are produced by competing interest and powers, deliberation promises much: more trustworthy and legitimate forms of political authority based on inclusive and unconstrained dialogue, more informed political judgements and decisions, and a more active account of citizenship (Warren, 1996). Proponents claim that deliberation can play a useful role in situations of value conflict (Walsh, 2007). For example, more dialogues have been encouraged across racial lines in deliberative groups organised by localities in the US. Through deliberative discussions, people can identify both common and divergent interests, and, in doing so, propose multiple courses of action that increase the likelihood for stable and long-term decision-making (Romsdahl et al., 2018). Deliberation has been praised as a way to foster democratic governance, facilitate democratic communities, and create democratic citizens (Goodin and Niemeyer, 2003). What’s more, positive experiences of deliberation can encourage further engagement (Collins and Nerlich, 2015).

Although different definitions of deliberation exist, they commonly emphasise the vital role of talk, the behaviour that people share information or express opinions or feelings, in solving political conflicts and problems (Mansbridge et al., 2012). Talk has been argued as a crucial tool for the public to overcome the unrepresentative opinions of political elites (Page and Tannenbaum, 1996). As stated by Carpini et al. (2004), ‘talking in public is a form of participation, one that arguably provides the opportunity for individuals to develop and express their views, learn the positions of others, identify shared concerns and preferences, and come to understand and reach a judgement about matters of political concern’ (p. 319). Beyond talk, deliberation also requires citizens to exchange ideas and disputes about political issues (Rawls, 1997). It is also a strength of deliberation that participants modify their ideas and preferences through interaction and persuasion with others rather than through coercive actions (Dryzek, 2000).

Much research has focused on deliberation in face-to-face ‘mini-publics’ (e.g. Fishkin and Luskin, 2005), which are defined as ‘a class of institutions that directly engage citizens, promote democratic deliberation and have, at times, been institutionalised into contemporary decision-making processes’ (Grönlund et al., 2014, p. 9). The mini-publics ‘typically involve the random selection of citizens to participate in a forum that is (ideally) held over multiple days where discussion is facilitated to achieve the ideals of deliberation and information is provided, usually in the form of expert presentation’ (Niemeyer, 2014, p. 28). Another group of scholarship has studied deliberation in political institutions (e.g. Nanz and Steffek, 2005), and another group has studied mediated deliberation in offline settings (e.g. Ferree, 2002). The rise of social media has brought increasing scholarly attention to online deliberation (Friess and Eilders, 2015).

The ‘constructive deliberation’, such as mini-publics, is initiated and owned by authorities, decision-oriented, goal-oriented/strategic, discrete and supplementary, orchestrated and controlled, occurring in organised methodical forums, and in a top-down manner (Hammond, 2020). Unlike the constructive deliberation, Hammond (2020) proposed a ‘possible new type of deliberation’ and named it ‘disruptive deliberation’, which is characterised as initiated and owned by movements, discussion-oriented, open-ended, continuous and directive, organic and ‘messy’, in a plethora of social spaces and forms, and in a bottom-up approach. As Hammond (2020) suggested, ‘although deliberative democracy is widely recognized as incorporating both constructive and critical dimensions, the practice of deliberative mini-publics has tended toward the system-supporting, constructive side by marrying citizen engagement with the representativeness, professionalism, and efficiency of the conventional policy process’ (p. 226). In contrast, disruptive deliberation is ‘marrying the lay-citizen perspective with disruptive protest movements in the public sphere’ (p. 226). Although communication about political issues on social media is not necessarily related to social movements, the deliberation I focus on in this thesis is similar to this ‘disruptive deliberation’, except it is initiated and owned by the users as a whole rather than by particular movements (Hammond, 2020).

The role of everyday political talk in deliberation has been praised by a number of scholars, for example Barber (1984), Habermas (1984) and Kim and Kim (2008). ‘Everyday political talk’ is defined by Kim and Kim (2008) as ‘nonpurposive, informal, casual, and spontaneous political conversation voluntarily carried out by free citizens, without being constrained by formal procedural rules and predetermined agenda' (p. 53) and categorised as dialogue deliberation, in contrast to 'instrumental deliberation'. Here, 'instrumental deliberation' means the process 'through which experts in the political system and rational citizens in the public sphere make collective decisions based on public reasons and shared values' (p. 53), for example in formal settings at public meetings. Although they suggest that there are no clear-cut differences between dialogic deliberation with instrumental deliberation, they argue that 'informal everyday talk—which, at its essence is dialogic deliberation—is the prerequisite to purposive and rational deliberations' (p. 54), which aligns with what Barber (1984) advocated: everyday political talk plays an essential role in a strong democracy, as shown in Barber's (1984) example:

> Think of two neighbors talking for the first time over a fence, or two college freshmen talking over a first cup of coffee: there are no debates, no arguments, no challenges, no setting of priorities, no staking out of positions, no inventorying of interests. … There is only a 'getting to know you' and thereby 'getting to know us'—exploring the common context, traits, circumstances, or passions that make of two separate identities one single we. World leaders meeting at a summit will frequently devote an initial session to getting to know one another in very much this fashion, before they get down to the business of bargaining and exchange. (p. 184)

Similarly, Habermas (1984) suggested that dialogic deliberation is the fundamental basis of rational deliberation, as rationality is produced by communicative action, which refers to 'the interaction of at least two subjects capable of speech and action who establish interpersonal relations' (p. 85). Communicative action is not primarily purposive or success-oriented.

Accordingly, the literature on deliberation can be grouped into two camps. One emphasises 'a formal, procedural, representative, impartial, and consensus-oriented notion', i.e. **institutionalised discursive procedures**, such as parliamentary talk (Steiner, 2004) or 'deliberative polls' (Fishkin, 1991). The other asserts 'an informal, critical, citizen-based, personal, and understanding oriented notion' (Graham, 2009, p. 12), i.e. **informal discursive participation**. Informal discursive participation is 'important for long-term instrumental goals by building collective identities, mobilizing opinion around issues, and so forth' (Dahlgren, 2018, p. 2062), which is aligned with the goal of deliberation. My thesis focuses on informal discursive participation.

According to Friess and Eilders (2015), we can examine any types of deliberation from three dimensions: institutional input (features of platforms), such as 'algorithmic governance' (recommendation systems); communicative throughput (the process of deliberation); and productive outcome (results of deliberation). As I concentrate in this thesis on users' interactions and the content they generate, I do not analyse the technical features of Twitter as a platform. Multiple reasons exist for not studying the results of deliberation in this thesis. First, climate change is a complicated and long-lasting political issue, and it is hard to track the immediate outcome of the deliberation. Second, interviews or surveys are commonly used when studying the results of deliberation. But, when it comes to the many users on Twitter, these are hard to conduct, especially for individual researchers. Therefore, the features of platforms and the results of deliberation are not the focuses of this thesis. Rather, I emphasise the communicative throughput, i.e. the process of how participants communicate deliberatively. Deliberation in this thesis is therefore defined as **the informal online discursive process in which participants express their opinions and discuss with each other with the potential goal of achieving mutual and collective understanding about political issues**.

Everyday political talk on Twitter is a form of the informal discursive process, and it is crucial to ask whether the discourse on Twitter shows the potential of deliberation.

2.3 Debates on the deliberative potential of social media

Much has changed in societies around the world with the emergence of the Internet as a global network in the 1990s. Since then, polarised opinions and ongoing debates about the impact of the Internet on democracy have appeared. These camps can be broadly grouped into 'cyber-pessimists' (Davis, 1999) and 'cyber-optimists' (Janssen and Kies, 2005), and deliberation is also involved in the debates, as the debates are also about the capacity of the Internet to engender or foster deliberation.

The leading proponents of the 'cyber-pessimists' camp include Postman (1993), Keen (2007) and Siegel (2008). The 'cyber-pessimists' basically assert that the Internet undermines the commitment and respect required in deliberation. For example, the Internet has been criticised for its role as a tool of governance for legitimating political actions (Hill and Hughes, 1998). Furthermore, some scholars have suggested that the freedom and openness associated with online discourse have actually led to the fragmentation or polarisation of public space (Sunstein, 2009), and thus dispute the Internet's deliberative potential (Shapiro and Bolsen, 2019; Sunstein, 2007). Fragmentation stands for 'the idea that online conversations about politics are typically divided into a variety of groups, and that this division takes place along ideological lines with people only talking to those who are ideologically similar' (Bright, 2018, p. 17). Polarisation is partly due to fragmentation and misinformation on social media (Kubin and von Sikorski, 2021) and can be harmful to democracy from multiple aspects. For example, it can increase the centralisation of power (Lee, 2015) and dissatisfy the public (Wagner, 2021). This concern has also been understood in relation to ‘selective exposure’, a practice in which users seek opinion-reinforcing content and avoid contradictory information, which is seen as problematic to deliberation (Sunstein, 2009; Freelon, 2013). Criticisms of social media for deliberation include ‘echo chambers’, fake news, highly targeted political advertising, computational propaganda, and hate speech (Margetts, 2019). For example, echo chambers are defined as ‘environments in which the opinion, political leaning, or belief of users about a topic gets reinforced due to repeated interactions with peers or sources having similar tendencies and attitudes’ (Cinelli et al., 2021, p. 1). According to the law of group polarisation stated by Sunstein (2002), echo chambers tend to reinforce an existing opinion within the group and move the group towards a more extreme position, which endangers deliberation.

By contrast, the ‘cyber-optimists’ argue that the lack of temporal and geographical restrictions encourages greater engagement in political issues online, and technological changes provide new opportunities for direct democracy (Boehmke and Bowen, 2010), likewise for deliberation. For example, Rheingold (2000) stated that people who have never seen each other in the flesh can create virtual communities, within which they exchange information and share emotional experiences in real time or extended periods, and organise collective political actions. Some scholars argue that the technical characteristics of the Internet create a virtual space that, for the first time, provides the ideal conditions for deliberation (e.g. Dahlberg, 2001; Dahlberg, 2007; Wright and Street, 2007). The ideal of deliberation sympathises with Barber’s (1984) ‘strong democracy’, which ‘stresses broad scale participation in political decision making and the activation of “citizenship” in determining outcomes’ (Niemeyer, 2007, p. 349). Authors like Pateman and Hume (1970), Barber (1984) and Habermas (1989) have provided the theoretical framework for intellectual reflections on how the Internet may foster democracy. Among them, Habermas’s notion of the public sphere provides a cornerstone for deliberative political communication (Habermas, 1989). The ideal is open pathways for information acquisition and equitably distributed deliberation among a wide swathe of the public (Shapiro and Park, 2018). With high hopes by politicians and scholars for strengthening processes of ‘deliberative democracy’ in a Habermasian sense (Habermas, 1989), the optimistic perspective on the Internet as an inherently democratic medium gave rise to the concept of ‘online deliberation’ (Thimm et al., 2012). For example, Dahlberg (2001) examined and claimed that the Internet is ‘enhancing and extending the public sphere of rational-critical discourse as conceived by advocates of deliberative democracy’ (p. 17). More precisely, the Internet has often been considered to provide an infrastructure for the public sphere that deliberative advocates have dreamed of (Graham and Witschge, 2003).

One important aspect of the democratic promise of online discussions is that individuals can actively generate, circulate and evaluate ideas. Some researchers have stated the potential benefits of social media for deliberation by arguing that online discussions have diminished the influence of social status and symbolic pressure on participants (e.g. Pruijt, 2002; Coleman, 2004). Online deliberation emanates from everyday life in the new social context, while not being constrained by current conventions and social settings (Thimm et al., 2014), so that expands existing communication systems, as the general public, not only political elites, are able to express their social-political concerns. Compared to obscure scientific papers and newspaper articles generated by gatekeepers, social media is ‘a forum where individuals of diverse backgrounds can share their thoughts and opinions’ (Cody et al., 2015, p. 1). Group experiments indicate that physical absence in online discussions contributes to more positive interactions between participants, compared with face-to-face discussions (Stromer-Galley, 2003). Furthermore, according to Talpin and Wojcik (2010), ‘both online and face-to-face deliberation definitely have a learning impact on actors, a vast majority of participants declaring that they had learned about climate change, other related issues, or the way to express their opinions’.

Researchers have identified a positive relationship between online discussions and voting (Mossberger et al., 2007), between social media and political participation (Boulianne et al., 2020) and between online-based deliberation and political behaviour (Gainous et al., 2013; Shah, 2016). Specifically, Semaan et al. (2014) studied social media use for political deliberation through a longitudinal interview study with 21 United States citizens, and found that, through multiple tools, people were ‘serendipitously exposed to diverse political information, constructed diverse information feeds, disseminated diverse information, and engaged in respectful and reasoned political discussions with diverse audiences’ (p. 1412). Unlike in the polarisation perspective, they also provided evidence that people were, at least in the early 2010s, intentionally finding diverse information and discussion partners (Semaan et al., 2014).

The jury is still out, but more insight from more data is required. Mining unprecedented amounts of data from social media enables us to discover features of user behaviours, opinions and interaction dynamics much more quickly (Barbier and Liu, 2011). Regardless of whether a researcher is a cyber-optimist or a cyber-pessimist, however, there is a significant possibility to be explored, namely that the opportunity to get access to other arguments online increases heterogeneous discussion (Collins and Nerlich, 2015). I argue that we can verify the deliberative potential of social media by a deeper exploration of users’ interactions and user-generated contents. Within the examination of online deliberation is a key discussion on the deliberative potential of Twitter.

2.4 Twitter

2.4.1 The deliberative potential of Twitter

Compared to the mass media, the 'two-way, relatively low cost, semi-decentralized and global communications' on the Internet, according to the cyber-optimists' position, potentially contributes to deliberation (Dahlberg, 2007, p. 49). On social media, which refers to 'Internet-based channels that allow users to opportunistically interact and selectively self-present, either in real time or asynchronously, with both broad and narrow audiences who derive value from user-generated content and the perception of interaction with others' (Carr and Hayes, 2015, p. 50), the distinction between senders and receivers is blurred in the many-to-many communication (Schäfer, 2012). This change is significant to the way how professionals, celebrities, politicians and the general public interact and communicate, and can potentially contribute to deliberation. For example, it has been revealed that journalists express opinions and interact with followers more freely on Twitter than through newspapers (Lasorsa et al., 2012), and more individuals and groups concerned with environmental issues rely on social media compared to mass media like newspapers or television (Karpf, 2012). Social media has transformed political discussions on multiple topics, including climate change (Fownes et al., 2018), and changed the structures within which meaning-making takes place (Pearce et al., 2015). For example, despite the existence of climate scepticism, extreme weather events prompt a surge in climate-related Twitter activities, and this increased attention may contribute to the response to climate change impacts (Fownes et al., 2018). As stated by Bennett (2003), social media 'may be changing the political game in favour of resource-poor players who, in many cases, are experimenting with political strategies outside of conventional national political channels such as elections and interest processes' (p. 144). By not being designed to ensure that audiences are 'on message' (Dryzek, 2000), social media may instead help people become collectively engaged with a task and enable them to acquire knowledge to address it (Pallett and Chilvers, 2013). It has been argued that mass media has strong effects on the audience by constructing social reality, i.e. 'by framing images of reality … in a predictable and patterned way' (McQuail, 1994, p. 331). Entman (1993) defined framing as 'select[ing] some aspects of a perceived reality and mak[ing] them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described' (p. 52). We can compare the discussion networks and framing on social media with what it looks like in the mass media era, as shown in Figure 2-1.

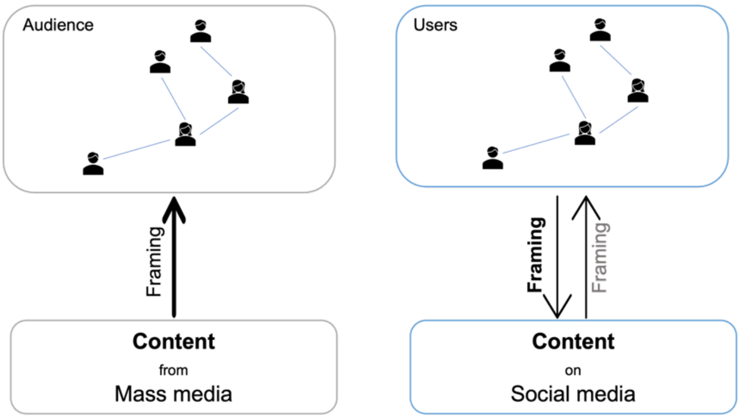

Figure 2-1. The differences in discussion networks and framing between the mass media and social media eras

Note: though the characters in the upper boxes are the same, it does not mean the components are perfectly the same. There are different types of users and diverse networks in each era.

In the mass media era, the audience was influenced by media, such as newspapers and television news. Political elites and interest groups significantly impacted content framing. Although there are some rules and algorithms on social media, both publics and elites (e.g., political elites, interest groups and journalists) have nominally equal access to the platform. They collectively generate content and influence the content they generate through information sharing and discussions. According to Himelboim (2008), online discussions contribute to democracy by enabling individuals to be 'more than a passive audience' (p. 158). In other words, social medial users have some power – either collectively or perhaps individually – to frame issues. Or to turn this around, we can exame social media's deliberative potential through analysing users' framing. From an empirical perspective, another difference is that research is far easier in the social media era. For example, if we want to study the discussion networks or content that audiences discuss with each other, we might have needed to conduct a survey or interview in the mass media era. In contrast, it is possible that we collect (big) data from social media without interacting with users with the help of big data techniques.

Factors impacting deliberation on different social media platforms vary. For example, Halpern and Gibbs (2013) analysed 7,230 messages on Facebook and YouTube to examine factors that might have influenced the quality of deliberation on the Obama White House's social media accounts and found that discussions among users on Facebook are more reciprocal, as they are exposed to content posted by their contacts, while the more anonymous and deindividuated YouTube is blamed for higher impoliteness. However, as argued by Fownes et al. (2018) and others (e.g. Lazer and Radford, 2017), studying different social media platforms together but overlooking platform-specific features may make interpretations confusing. Therefore, I focus on one social media platform in my thesis: Twitter.

Twitter, a microblogging platform that allows users to generate and share content such as text, images and videos with others, has been one of the most popular social media platforms of the last decade since its launch in 2006. Twitter is unique as it enables users to interact via replies and mentions with others with whom they are not actually connected (Hodges and Stocking, 2015). It provides a platform and possibilities for a diverse range of actors to exchange ideas. In addition to Twitter's role in political communication and participation, some scholars have noted the potential of Twitter as a communication medium for political deliberation (Kim and Park, 2012). As proposed by Cohen (1997), 'the ideal deliberative procedure' sketches three general aspects of deliberation: '[t]here is a need to decide on an agenda, to propose alternative solutions to the problems on the agenda, supporting those solutions with reasons, and to conclude by settling on an alternative' (p. 73). Being decentralised, user-focused and user-led, Twitter potentially incorporates ideal principles for deliberation (Flew, 2008). Deliberative theory suggests that repeated interpersonal interactions where individuals engage in extended conversation may have substantial effects (Habermas, 1989). Twitter's default settings allow for studying this kind of back-and-forth discussion among users instead of only a single utterance (Stewart, 2018). Some scholars have emphasised Twitter's role as a networked agent within the protest space, such as Segerberg and Bennett (2011). Rather than focusing on Twitter's role itself, in my thesis I study the interaction and content generated on Twitter.

In Schmidt's (2014) sense of 'personal publics' on Twitter, 'information is selected and displayed according to criteria of personal relevance (rather than following journalistic news factors); information is addressed to an audience consisting of network ties and is made explicit (in contrast to being broadcast to an unknown mass audience), and information is often disseminated in a conversational rather than unidirectional way' (p. 4). Twitter as a medium for political deliberation facilitates political discussion among users (Kwak et al., 2010) and it possibly enables a 'direct communication channel between politicians and citizens' and boosts political movements as a tool of 'political communication and mobilization' (Kim and Park, 2012).

As mentioned in Section 2.2 above, I focus on the communicative throughput (the process of deliberation) and, more specifically, on the informal discursive process. Accordingly, my thesis examines deliberation on Twitter by analysing the structure of discussion networks of users, the content they generated, and the difference of content generated by user groups. I will illustrate each aspect in the following sections.

2.4.2 Discussion networks on Twitter

As mentioned in Section 2.2, it is crucial to ask whether the discourse on Twitter shows the potential of deliberation. Discourse is defined as ‘the actual use of language along with other multi-model resources (e.g., facial expression, gazes, gesture, body movements, artifacts, and the material settings) to accomplish actions, negotiate identities, and construct ideologies’ (Waring, 2017, p. 8). This thesis focuses on the use of language, i.e. the tweets users posted and users’ interactions through tweets.

Before talking about discussion networks on Twitter, we first need to explore features of the interactions on it. Users have other goals and motivations when choosing different kinds of interactions, i.e. following, retweeting, mentioning and replying (Williams et al., 2015). Through retweeting, users share information with their followers. Retweets can show endorsement, allowing users to raise the content’s visibility by spreading content generated by other users (Boyd et al., 2010). A mention is a tweet that contains other users’ names, starting with @. Mentions address specific users directly through the public feed (Honey and Herring, 2009). Only when the tweet begins with the @ sign (i.e. the other user’s name is at the beginning of the tweet) does it register as an @reply. Hansen et al. (2019) technically distinguish replies and mentions on Twitter: ‘Twitter makes a technical distinction between @replies and @mentions. The Twitter infrastructure only keeps track of replies, for discussion threading purposes, and not of @mentions’ (p. 147), and they clarify that ‘@replies as a subset of @mentions—all @replies are @mentions, but not all @mentions are @replies’ (p. 147).

It is worth noting that the functions might have changed within different data periods, and between data collection and the completion of this thesis, as Twitter continues to change how its service works. Conover et al. (2011) found Twitter networks more clustered when using retweets as edges than when using reply/mention networks. When it comes to topics that the wider public engaged, more clustered networks can increase the complexity of the analysis. Regardless of the noisy environment on Twitter, @replies as a ‘marker of addressivity’ (Honey and Herring, 2009, p. 1) make discussions coherent, in other words enable users to track discussions (Hansen et al., 2019). Replies are valuable ties among users, as individuals benefit from others' knowledge (Himelboim, 2008). Arguello et al. (2006) proved that people receiving replies from others are more likely to continue and engage in the discussion. Williams et al. (2015) stated that they 'consistently observed strong attitude-based homophily in follower and retweet networks, but much less consistent and weaker homophily in mention networks'. Reply networks were included in their mention networks because they did not distinguish between these two. But they did note that there are two kinds of mentions in the networks; as they said, 'mentions can also form part of a discussion or conversation, or offer (possibly critical) comment on the target user's activities or expressed attitudes'. According to this evidence, and following Himelboim (2008), who stated that a discussion on Twitter could be conceptualised as a network of participants and their reply-based relationships, in this thesis the discussion network means specifically networks constructed by replies.

Communication thinking has been influenced by the network perspective since the 1970s (Shumate et al., 2016). Shumate et al. (2016) define communication networks as 'relations among various types of nodes that illustrate the ways in which messages are transmitted or interpreted'. There are many interesting studies that have engaged the communication process in social networks, although they were not recognised as communication studies at that time. For example, in Granovetter's (1973) famous work, 'the strength of weak ties', which examines whether the strength of network ties between people had an impact on finding a job, the flow of job information is undoubtedly a type of communication. Also, in Lazega and van Duijn's (1997) study looking at the relationship between advice-seeking behaviours and the positions in the formal structure (status, seniority etc.) in a law firm, the advice-seeking behaviours are also communication behaviours. Some researchers in social network analysis think social exchange provides people information that broadens and deepens their engagement with politics (e.g. Huckfeldt, 1984). Informal discussions in social networks disclose political information to network partners, and consequently influence their participatory decisions and can make them more active in politics (McClurg, 2016). McClurg (2016) extrapolated the approach to participation and proved that informal social interaction influences people's decisions about political participation with political information.

Discussion networks contribute to democracy by allowing users to participate in political conversations while exposing them to conflicting ideas (González-Bailón et al., 2010). There have been rich studies on the influence of offline social networks on deliberation. For example, based on the survey results of 1,263 adults in the US, Goldberg et al. (2019) showed that conversations in offline social networks build an understanding of climate change and impacts, and empower people to be more open with those around them. Guilbeault et al. (2018)

conducted an online experiment to test the influence of bipartisan social networks on how individuals interpret climate information from NASA, and found that, when individuals are exposed to conflicting ideas in bipartisan social networks, the polarisation can be reduced. Researchers have also attempted to apply social network analysis in online deliberation. For example, Kim and Park (2012) used it to study online political participation and deliberation through South Korean politicians' behaviours on Twitter.

Social network analysis has already been applied to analyse individual roles, as well as the dynamics and structures of online discussion networks (Himelboim, 2008). Social network analysis can contribute to communication studies in many ways. For example, with the help of network graphs, the process of information flow and exchange can be shown clearly. Also, the measurements in network analysis can be used to identify the important roles in communication.

Mapping Twitter discussion networks can provide important insights into a public discussion over a societal or political issue, without or before engaging in any kind of text analysis (Barisione et al., 2019). So, interest in Twitter is not only in the content of discussions themselves but in the conversational relationships between participants. Chapter 4 focuses on testing the deliberation of the discussion of climate change on Twitter. Instead of testing the content or arguments in the discussion, I concentrate on the structure of discussion networks.

2.4.3 Framing on Twitter

Besides examining the structure of discussion networks, the content that users generate is also valuable for us to explore deliberation on Twitter. Chapter 5 and Chapter 6 take framing as a framework to investigate the user-generated content.

Framing theory rests on the premise that we can examine an issue from multiple perspectives and interpret it with different concerns (Chong and Druckman, 2007). However, the field of framing studies has struggled to reach a consensus on the definition of frames. Gitlin (1980) argued that a frame is built through selection, emphasis and exclusion. As Graber (1984) demonstrated, individuals strategically manoeuvre to 'tame the information tide'. The effect of framing is to prime values differentially via establishing the salience (Sniderman et al., 1991), which means 'making a piece of information more noticeable, meaningful, or memorable to audiences' (Entman, 1993, p. 53). Frames construct issues, as they make plain the core of the issue, propose how it should be conceptualised, and might influence what action should be taken to solve the problem (Entman, 1993). According to Gamson (1992), people construct their understanding of issues using the symbolic resources available to them in everyday lives and combine these symbolic resources differently in different situations. Subsequently, Entman (1993) defined framing as 'select[ing] some aspects of a perceived reality and mak[ing] them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described' (p. 52). I follow this camp, led by Gitlin, Graber, Entman and Gamson, in this thesis. Pan and Kosicki (2001) argued that 'public deliberation is not a harmonious process but an ideological contest and political struggle. Actors in the public arena struggle over the right to define and shape issues, as well as the discourse surrounding these issues' (pp. 35–36), and the authors regarded framing as a strategic action in public deliberation, which indicated that framing is a crucial component of deliberation, which also impacted my definition of framing in this thesis.

According to Chong and Druckman (2007), frames can be classified as frames in thought, i.e. dimensions influencing an individual's evaluation in their minds, and frames in communication, i.e. the main concerns underlined in the talks. Frames in thought are also defined here as 'frames of individuals' (Ardèvol-Abreu, 2015): 'frames of interpretation of reality and schemas in which new information is integrated, so they do not have a physical manifestation (like media frames do), but can have an influence on the attitudes and behaviour of individuals. These are psychological processes influenced by sociological factors such as culture' (p. 423). Frames in thought are important, because they impact individuals' opinions; however, rather than studying this psychological dimension, my thesis only focuses on frames in communication.

To summarise, my definition of framing is **a strategic action whereby individuals select some aspects of issues and make them more salient in communication**. Following Pan and Kosicki (2001), I argue that framing is an important component of deliberation, especially on social media, where users have more power to impact the framing.

No matter who is using frames, frames in communication are 'never neutral', because '[i]nterests, principles, partisan attachments, ideological convictions, and more all figure into the views that citizens express toward matters of public life' (Nelson and Kinder, 1996, p. 1055) and 'they define an issue, identify causes, make moral judgments, and shape proposed policy solutions' (O'Neill et al., 2015, p. 380). Lots of research about frames in communication focus on the 'framing effect', which is typically about 'how frames in the communications of elites (e.g., politicians, media outlets, interest groups) influence citizens' frames and attitudes' (Chong and Druckman, 2007, p. 109). However, citizens' frames in communication are also crucial for us to know how they make strategic choices when participating in particular political issues. Researchers have identified the importance of framing in mobilising interested and bystander publics to influence decision-makers, and in shaping public understanding of controversial technologies (Stelmach and Boudet, 2021).

My thesis focuses on how the population of Twitter users collectively frame climate change using hashtags (Chapter 5), and then I zoom in on how the different user groups that I identified from all the engaged users in the topic differently frame an emerging technology related to climate change that removes carbon dioxide to mitigate climate change, that is, negative emissions (Chapter 6).

Previous scholarship in framing studies has been criticised for tending to treat frames as static, while in fact, time is an important aspect (Benford, 1997). Some researchers have focused on framing as a dynamic process (e.g. Stelmach and Boudet, 2021). I will take ‘time’ into account in Chapter 6.

2.4.3.1 Hashtags and framing

Hashtags, denoting any characters following a ‘#’ symbol in tweets, are a ‘community-driven convention’ that gained ground in 2007 during the San Diego forest fires (Small, 2011). ‘Hashtags are a kind of “folksonomy”, a tagging system emerging from the free social tagging of information and objects’ (Eriksson Krutrök and Lindgren, 2018, p. 2). To include one in a tweet is also taken as a ‘performative statement’ as ‘it brings the hashtag into being at the very moment that it is first articulated, and—as the tweet is instantly disseminated to all the sender’s followers—announces its existence’ (Bruns and Burgess, 2015, p. 23). Hashtags can promote the circulation of specific topics and help users gather around common interests or activities. Because users can start a discussion with a hashtag, others can join the discussion using tweets that include that hashtag without following relationships with others (Bruns and Highfield, 2015). As stated by Segerberg and Bennett (2011), ‘[u]nlike the profile feed, which is controlled by a particular actor, the community-generated hashtag convention allows anyone to use a hashtag for any tweeted message whatsoever’ (p. 203). The ‘technological affordance’ of hashtags enables many users to participate in the mass discussion on Twitter at once (Eddington, 2018). Rambukkana (2015) regarded hashtags as ‘technosocial events’ to ‘think through how we can understand hashtag-mediated discursive assemblages, and suggests that we can see hashtags as ‘an open and non-predefined set of communicative encounters and architectures, a crossroads between form and matter, medium and message entangled’ (p. 4).

Social scientists have taken hashtags as a marker of topics (Rzeszotarski et al., 2014), representation of the context of a tweet (Tsur et al., 2012) or a tag of a user's community membership (Yang et al., 2012). Hashtags can 'enrich communal bonds between networked Twitter users', despite cultural affiliation (Brock, 2012, p. 544). Rather than through follower/followee relations or formal organisations, users of the hashtag, defined by Bruns and Burgess (2015) as 'ad hoc publics', come together through 'ambient affiliation' (Zappavigna, 2012), that is, through rendering the language searchable and upscaling the call to affiliate with values expressed in the tweet.

According to Rambukkana (2015), there are two kinds of investigations of hashtags in political communication. There are top-down investigations, focusing on hashtags as a political technology broadly, looking at tags such as #auspol (Sauter and Bruns, 2015), a popular hashtag related to Australian politics, and #cdnpoli (Small, 2011), the most popular hashtag of Canadian politics. 'By adding the #auspol hashtag to a tweet, a user decides to trigger an algorithm in the Twitter software base, which associates the tweet—and, by extension, the user—with a particular topic and group of participants. In this way, users add to a publicly visible body of data: they contribute to the negotiation of truth via public debate and thus participate in the construction of knowledge' (Sauter and Bruns, 2015, p. 57). Also, there are bottom-up investigations, looking at hashtags for discussing the grounded politics of particular groups of political actors within or across geographical areas, such as #agchatoz (Burgess et al., 2015), a hashtag for Australian farmers to discuss agricultural issues. Hashtags are also used to mobilise for activist causes. 'Hashtag activism' is defined as the 'act of fighting for or supporting a cause with the use of hashtags as the primary channel to raise awareness of an issue and encourage debate via social media' (Tombleson and Wolf, 2017, p. 15). 'Hashtag activism as a form of participatory culture enables individual users to form groups around particular topics and events' (Xiong et al., 2019, p. 12). For example, Eddington (2018) examined the relationship between Donald Trump and extremist and white supremacist groups in the discursive networks by analysing Twitter hashtags' semantic network.

As the operator # in hashtags explicitly reflects users' emphasis, which can be regarded as an indicator of framing, several studies have adopted hashtags as frame markers (e.g. Meraz and Papacharissi, 2013; Papacharissi and de Fatima Oliveira, 2012) to help, as they argue, to eliminate researchers' subjectivity in frame detection (Shi et al., 2020). However, rather than taking all the single hashtags as frame markers, in Chapter 6 I will explore the framing evident in hashtag co-occurrence networks. Users often associate different hashtags in the same tweet, which gives birth to hashtag co-occurrence networks, to trigger others' attention about their comments, or to join different subconversations to frame the overall topic in a particular way.

Compared to the ‘primary actors’, i.e. Twitter accounts for organisations and individuals, hashtags are regarded by O’Neil and Ackland (2018) as ‘secondary actors’, because they need agency to make connections with other actors. ‘Primary actors also promote issues via the use of hashtags and, in doing so, create ties between these issues in semantic space (two hashtags are connected in semantic space if a Twitter user features both hashtags in a tweet)’ (O’Neil and Ackland, 2018, p. 15) Further, the authors differentiated ‘field hashtags’, which show that the actor is connecting to the issue or frame and all the participants are ‘equally likely to use’, from ‘frame hashtags’, ‘which are only likely to be used by a networked public that is pushing a particular frame’ (p. 15). In this thesis, #climatechange is a field hashtag, as it defines the boundary of the topic on Twitter. Participants in the field hashtag #climatechange, so-called ‘hashtag publics’ by Rambukkana (2015), create ties between different hashtags within the semantic space to frame the issue to the direction they want to.

Scholarship into hashtag use tends to focus on analysing the diffusion of one particular hashtag or the role of the same type of hashtags to explore the features of a social movement (e.g. Papacharissi and de Fatima Oliveira, 2012; Meraz and Papacharissi, 2013; Moscato, 2016). However, less is known regarding how hashtags of different nature or thematic types may frame the upper-level topic (e.g. climate change), rather than the narrow topic (e.g. a social movement), differently and how users connect different hashtags together to frame the political issues. Analysing hashtag co-occurrence networks helps to identify the relative prominence of individual hashtags and the strategies are taken by users to frame the political issue (Wang et al., 2016).

Hashtags can be categorised differently. They may stand for geographical locations (#Australia), politics (#trump), conferences (#COP24) or social movements (#climatestrikes), or operate as an ‘affective amplifier’ (Eriksson Krutrök and Lindgren, 2018, p. 3) (#happy, #sad). Bruns and Moe (2014) differentiated between topical hashtags and non-topical hashtags. Topical hashtags are markers of an event, an issue or a topic, which contribute to a discussion on a particular topic, which can be long-standing themes (e.g. #auspol), backchannels to TV events (e.g. #masterchef) or reactions to particular issues or events (#royalwedding). Non-topical hashtags such as #facepalm or #fail are emotive markers and can be applied to any tweet type, which vary from the initial intent of the use of hashtags but still contribute to the communication. Rocheleau and Millette (2015) categorised hashtags in their dataset as political markers, topical markers, location markers, etc.

However, the kinds of hashtags that have been used in the topic of climate change on Twitter, and what roles different types of hashtags play in the discourse, have not been studied yet. Chapter 6 answers these two questions from the perspective of network analysis to find out how hashtags are connected to each other for the collective sense-making in the topic of climate change and the roles of different kinds of hashtags in the process. I focus on networks of the hashtags co-occurring with #climatechange.

2.4.3.2 User groups and framing

As mentioned above, frames in communication are never neutral, and individuals select certain aspects of the issue and make them salient in the conversation. Similarly, the user groups they belong to also have different interests, or, in other words, their interests bring them together to form groups.

Nelson and Kinder (1996) stated that 'public opinion on matters of government policy is group-centric: shaped in powerful ways by the attitudes citizens possess toward the social groups they see as the principal beneficiaries (or victims) of the policy' (pp. 1055–1056), and that the group-centrism is essential to public opinion on various political issues. Also, as mentioned in Section 1.1, Converse (2006) suggested that visible social groupings may have the function of centralising citizens' political thinking to simplify the ways to comprehend complicated political issues. The statements in these two studies indicate the important role of groups in political issues. I argue that it is crucial to understand the ways groups collectively frame issues in processes of deliberation.

My Chapter 6 classifies users into different groups according to the self-descriptions on their Twitter profiles, and then, with the help of structural topic modelling, an unsupervised text analysis method, to identify the frames that they used when they tweeted about negative emissions. By doing so, I can compare the different frames these user groups used and find their strategies for 'constructing' this emerging issue.

2.5 Online deliberation and climate change communication

2.5.1 Climate change as a political issue

Despite nearly universal consensus in the scientific community that a causal relationship has been proved between human activity and climate change (IPCC 2015), conflicting views on climate change exist. Differences in values and worldviews make science, information and education less helpful to counter polarisation (McCright et al., 2016), because ‘human skills for reasoning are developed more to meet our social needs, rather than individual abilities to understand a problem, such as climate change’ (Romsdahl et al., 2018, p. 278). Even when faced with the same information, individuals can respond differently according to their values and worldviews, which indicates that deliberation is the key to conquering polarisation and achieving sustainable discussions in climate change communication, rather than information (Collins and Nerlich, 2015).

Climate change has been described as a ‘super wicked’ problem by scholars such as Levin et al. (2012) and Kahane (2018), because it is hard to solve with traditional responses, which ‘work from problems to solutions: the problem is defined, outcomes and outputs determined, implementation plans designed, and performance targets specified’ (p. 9). Because of their ‘non-linear and unpredictable trajectories, wicked problems defy such approaches to problem solving’ (p. 9); on top of that, climate change has additional troublesome features, for example, running out of time; causes and solutions being provided by the same objects; and non-existent or weak central authority that can solve the problem.

As a wicked problem, climate change creates a dilemma: ‘even when we collectively recognize the need to act now to avoid the catastrophic impacts, the immediate implications of required behavioural changes overwhelm our collective interest in policy change and the ability of the political and policy systems at multiple levels to respond’ (Levin et al., 2012, p. 148). Also, the climate and its development are hard for people to observe directly, and the social influence of climate change is debatable (Schäfer, 2015). As argued by Lorenzoni and Pidgeon (2006), ‘how “danger” is interpreted will ultimately affect which actions are taken’. However, governments engaged in policies related to climate change have different structures and interests. Even within a country, different parties stand for different interests and have their own emphases. When it comes to a global issue, it takes longer to negotiate the whole process to get standard policy done. It shows in the ‘tragic response’ to climate change: ‘too many times, climate agreements have become merely aspirational statements that are largely ignored after they are signed because those most responsible for and able to address this global predicament must get back to business as usual' (Kahane, 2018, p. 10).

Studies have revealed that climate change communication has contested different interests and purposes. Scholars have observed that, particularly in anglophone countries – the UK, the USA and Australia – climate change has become more of a politicised issue over the last two decades (e.g. Painter, 2011). As stated by Anderson (2009), climate change is a 'deeply contested area', with 'considerable competition among (and between) scientists, industry, policymakers and non-governmental organizations (NGOs), each of whom is likely to be actively seeking to establish their particular perspectives on the issues as the one to be adopted' (p. 166). The United States, the United Kingdom and Australia are known for advocating for no actions using the power of frames; for example, Moser (2010) argued that '[t]he skilful use of responsibility, economic conservatism, uncertainty, and related frames has served to create persistent doubt in audiences' minds about the reality and urgency of the issue, and about key messengers' (p. 39). Democrats or liberals tend to believe in the existence of anthropogenic climate change, while Republicans or conservatives tend to reject it (Druckman and McGrath, 2019). Jasny and Fisher (2019) surveyed policy actors working on climate change in the US to find out how climate denial dominated climate politics under the Trump administration, and proved that echo chambers still play a vital role in communication networks among American policy elites. It also has been revealed that conservative think tanks in the United States have published or supported the publishing of most books attacking climate science and scientists, of which most have not been peer-reviewed, and play a major role in climate scepticism (Dunlap and Jacques, 2013). Meanwhile, some studies indicate that climate scepticism might be a phenomenon of Anglo-American culture and less of a problem in other countries, at least in Germany (Engels et al., 2013).

2.5.2 Deliberation and climate change

Deliberation especially needs to engage the general public, which has a variety of values and concerns when it comes to problems such as climate change that affect everyone and prove complicated to solve. As argued by Kahane (2018), deliberation is able to 'serve to integrate those differing perspectives and values, and thus support citizens in expanding their circle of concern as well as, crucially, stimulating and organizing input on the condition of their community and the ecological systems that enable its existence' (p. 226). As argued by Niemeyer (2013), deliberation contributes to 'make salient the environmental dimensions of issues' (p. 434). Through deliberation, citizens can be attuned to environmental complexities and be able to reflect on the issue with a long-term view (Niemeyer, 2014). According to

Bedsted and Klüver (2009), when citizens engage in deliberation, their preferences become more sensitive to climate change and demand stronger global action. 'If successful, deliberation not only promises to transform the possibilities for action on climate change, but also to build the capacity to respond by improving the underlying conditions for environmental governance' (Niemeyer, 2013, p. 429). More specifically, deliberation offers a pathway to surmounting the divisive and polarised nature of the climate change debate (Whitmarsh, 2011). In this view, deliberation offers a way to focus on more substantive issues and improve the ability of citizens to better deal with the kind of complexity associated with climate change. This is because, for most participants, the deliberative setting provides the environment in which information can be acquired and provides the incentive structure to engage with that information (Goodin and Niemeyer, 2003). Deliberation promises a political environment within which the plurality of environmental values can be effectively and sensitively assessed and considered in decision-making (Warren, 1996).

The important role of the general public in solving the problem of climate change has been stated by some scholars, because climate change is not an issue that relies solely on the governments or scientists. According to Lorenzoni and Pidgeon (2006), it is vital to take public views into account when making decisions on climate mitigation for three reasons: (1) the acceptance of the public is needed for successful policy implementation; (2) it is easier for communication when public policy and citizens' frames of reference are similar; and (3) the public might misunderstand or ignore the implementation. Niemeyer (2013) demonstrated that the general public is actually 'the basic ingredients for action on climate change' based on empirical evidence, and it is crucial to 'democratize public discourse along deliberative democratic lines' (p. 431). 'Deliberation increases the salience of common-good issues and engenders deeper forms of cognition on complex issues in ways that produce outcomes reflective of a strongly held, if latent, desire to achieve action consistent with long-term management of and the need for urgent action on climate change' (Niemeyer, 2013, p. 448). According to Black et al. (2008), deliberation makes it possible to raise the bar in citizens' assessment of the complex issue of climate change and helps to change both the conditions under which the issue could be governed and citizens' expectations in a democratic system. In other words, deliberation can enhance the tendency to view the issue of climate change through the lens of collective identity in solving a common-good problem. However, improving environmental outcomes may require not achieving ideal deliberation in all sites in the public sphere but rather developing the capacity to avoid the distortion of public opinion by entrenched interests (Niemeyer, 2011).

2.5.3 Climate change on social media

Media plays an important role in climate change communication. As stated by Carvalho (2010), ‘the media are both important arenas and important agents in the production, reproduction, and transformation of the meanings’ (p. 172). Nisbet (2009) argued that framing is an important communication tool for engaging the public around climate change. ‘Frames help to render events or occurrences meaningful and thereby function to organize experience and guide action’ (Benford and Snow, 2000, p. 614).

The majority of the present research about climate change communication has been about the coverage in the mass media, especially newspapers. As summarised by Schäfer and Schlichting (2014), a number of research studies have analysed media representation of climate change to different audiences since the early 1990s. For example, Djerf-Pierre (2012) analysed the attention paid to environmental issues by Swedish television news over 30 years, Schäfer et al. (2013) compared the coverage related to climate change in newspapers in Australia, Germany and India over 15 years, and Schmidt et al. (2013) compared data on the media attention in newspapers to climate change in 27 countries over 15 years.

Apart from this dominant camp focusing on mass media, a number of studies have started to focus on the issue of climate change on social media. As suggested by Hodges and Stocking (2015), ‘one potential impact of social media is its ability to broaden and sustain environmental networks and movement over time due to the flexibility and variety of approaches and interactions between various groups and the public’ (p. 229).

Some studies have focused on the role of organisations in climate change communication on Twitter. Abbar et al. (2016) collected all the climate change-related tweets posted between 2011 and 2016 by 117,000 users claiming to live in Qatar. One of the interesting findings of their study is that ‘organizing big events is not enough to raise any lasting public awareness toward climate change’ (p. 10). Another study analysed the energy-saving practices of communication on Twitter among 1,084 communicators, and revealed that, although organisations dominated in the communication, they could not substantially raise public awareness, and the information is mainly shared between organisations rather than reaching a different audience. The network analysis in this study suggests that it is beneficial to target the most influential groups to achieve maximum diffusion (Mohammadi et al., 2016).

Related to the role of organisations in climate change communication on social media, a group of scholars has focused on the frames used by social movement organisations or environmental movement organisations, so-called ‘collective action frames’. In the movement framing literature, a ‘collective action frame’ is defined by Benford and Snow (2000) as an ‘action-oriented sets of beliefs and meanings that inspire and legitimate the activities and campaigns of a social movement organization’ (p. 614), of which the key framing tasks are ‘diagnostic framing’ (problem identification and attributions), ‘prognostic framing’ (articulation of proposed solutions or alternative arrangements) and ‘motivational framing’ (action mobilisation) (Snow and Benford, 1988). The literature on how ‘frames get made’ (Hart, 1996, p. 95) suggests that, besides the above three core framing tasks, frames are also developed and deployed by three overlapping process: discursive, strategic and contested. As mentioned above, this thesis is interested in the informal discursive process on Twitter. Although, rather than focusing on social movements or movement members, this thesis focuses on all the users who are engaged in the topic on Twitter (I call how the users frame the political issue on Twitter ‘collective framing’), it is still worth investigating what the movement framing literatures found about the discursive processes. As stated by Benford and Snow (2000), discursive processes refer to ‘the talk and conversations—the speech acts—and written communications of movement members that occur primarily in the context of, or in relation to, movement activities’ (p. 623), and collective action frames are developed and generated by ‘two basic interactive, discursive processes: frame articulation and frame amplification’ (p. 623). Frame articulation involves ‘connection and alignment of events and experiences so that they hang together relatively unified and compelling fashion. Slices of observed, experienced recorded “reality” are assembled, collated, and packaged’, and frame amplification involves ‘accenting and highlighting some issues, events, or beliefs as being more salient than others. These punctuated or accented elements may function in service of the articulation process by providing a conceptual handle or peg for linking together various events and issues. In operating in this fashion, these punctuated issues, beliefs, and events may function much like synecdoches, bringing into sharp relief and symbolizing the larger frame or movement of which it is a part’ (p. 623). I argue in Chapter 5 that the hashtag co-occurrence network involves both processes, as users select certain hashtags and connect them in different ways. The structural topic modelling in Chapter 6 aims to find out the frames from the words selected and posted by users in tweets, which involves frame amplification. According to Benford and Snow (2000), the key to understanding the dynamics of framing resides in the articulation and amplification. However, the problem is that studies of evolution of frames are ‘highly labor intensive, requiring not only field but access to and retrieval of the discourse that is part and parcel of the framing process’ (p. 624). This reflects the strengths of my Chapter 5 and Chapter 6, in which I retrieve data through Twitter API and utilise network analysis and machine learning techniques to ease the ‘labour intensive’ process.

It is definitely important to focus on the coverage of climate change on either mass media or social media, how organisations utilise framing, and the influence of frames on public opinion of climate change. But, at the same time, it is also crucial to know how publics express and frame climate change in their everyday conversations. The impacts of the general public on social media have been shown to be significant. For example, according to Newman (2016), non-elite users, such as individual bloggers and the concerned general public, are found to account for the majority of the most transmitted tweets about the release of Working Group 1's Summary for Policymakers of the Intergovernmental Panel on Climate Change Fifth Assessment Report, and most of them are focusing on public understanding of the report. Several studies have started to look at how people express their opinions about climate change on Twitter. For instance, Holmberg and Hellsten (2015) observed gender differences in using hashtags and usernames when talking about climate change, that is, female users appeared more certain about anthropogenic climate change and mentioned more campaigns and organisations, while males were more likely to be sceptical and mentioned more individuals. Cody et al. (2015) analysed tweets with the keyword 'climate' covering September 2008 and July 2014 using sentiment analysis, and found users happiness expressed in tweets changes when different events happened, and they also revealed that the hashtag 'globalwarming' is more used by climate deniers. Williams et al. (2015) categorised the most active users who talked about climate change in their dataset covering four months in 2013 as 'activist', 'sceptic' or 'neutral' and analysed their interactions. They demonstrated that the discussion of climate change on Twitter was 'characterized by strong attitude-based homophily and widespread segregation of users into like-minded communities' (p. 135).

There is a dearth of research that assesses the deliberative potential of the Internet and social media on the topic of climate change (Cagle and Herndl, 2019), let alone testing it statistically and structurally. Collins and Nerlich (2015) examined deliberation in user comment threads in response to articles about climate change in *The Guardian* online newspaper by corpus analysis, and found that, 'whilst some aspects of online discourse discourage[d] alternative viewpoints and demonstrate[d] "incivility", user comments also show[ed] potential for engaging in dialogue, and for high levels of interaction' (p. 189). Shapiro and Park (2018) tested whether elites were diminishing the deliberative potential of provocative topics on YouTube, by focusing on the structure of the discussions that follow the most popular climate change-related videos, and confirmed that discussions could be elite-driven. To fill this gap in our understanding of online deliberation, Chapter 4 will operationalise the measurements of deliberative potential in discussion networks about climate change on Twitter.

2.5.4 An emerging technological issue in climate change

The adoption of additional strategies like the removal of CO_2 (carbon dioxide) from the atmosphere has been identified as a potential pathway to climate change mitigation, and this process of drawing down CO_2 is known as negative emissions (NE) (Fuss et al., 2014; Minx et al., 2017). While NE has been identified as an significant potential solution, it remains in its infancy concerning scalable solutions (Minx et al., 2017). While the development of technological solutions is needed, those possible solutions need to be understood as to how they interact with social factors relating to acceptance and public attitudes (Buck, 2016; Minx et al., 2017; Colvin et al., 2019).

Deliberation is important before the significant commercial realisation of emerging technologies has been achieved with various publics engaged throughout the early stage of scientific research, development and issue framing (Rogers-Hayden and Pidgeon, 2007). For this reason, aside from taking climate change as an overall topic, this thesis also digs into emerging technologies related to climate change. This is necessary because climate change is a far more developed and complicated issue, and many noises in the climate change discussions exist; for example, people tend to talk about things less related to climate change with #climatechange to attract more attention from others as it is widely discussed. It is significant to investigate a newly emerging subtopic of climate change with specific user groups engaged. What's more, NE is a still narrower topic, with a more particular group of people engaged. In this sense, in a departure from Chapter 4 and Chapter 5, I focus on NE in Chapter 6, and take a different but complementary perspective to the other two case studies – focusing on different user groups' framing.

In sum, I have pointed out in this chapter that, to study the deliberative potential of Twitter, it is crucial to study the structure of discussion networks (a particular representation of discourse), the strategic choices that participants make when participating in conversations, and how different user groups frame the same issue differently.

The structure of Chapter 4 to Chapter 6 is shown in Figure **2-2**.

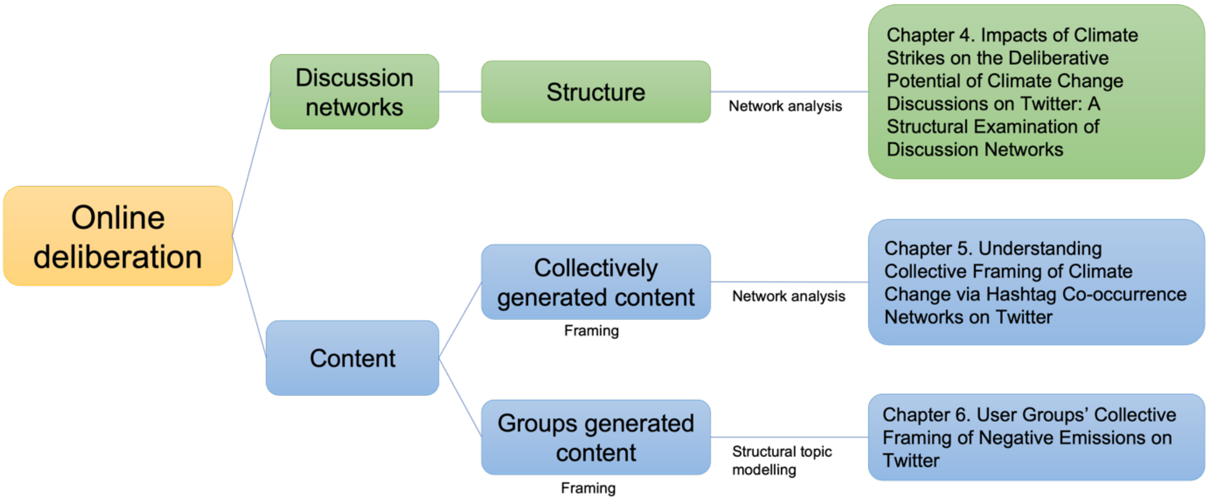

Figure 2-2. The structure of the case studies

Chapter 3 Methodology

3.1 Introduction

The epistemological orientation of this thesis is that users' online choices – statements, interactions, relationships to other users – can be taken as in some way indicative of the preference of those users. By studying user-generated contents on social media, we can examine users' online behaviours and preferences. The overarching research question of this thesis is: what is the potential of online discussions for deliberation? To answer this question, I need to collect the data that the users generated when discussing key issues ripe for deliberation (in this case, climate change) and measure the deliberative potential these data reveals.

As introduced in Chapter 1 (Introduction) and Chapter 2 (Literature Review), it is important to measure the deliberative potential of discussions of climate change on Twitter, because the role of Twitter in deliberation is still uncertain, and we need to understand participants' behaviours and the content they generate in climate change discussions. In this chapter, I discuss possible methodological options to answer the research questions, and introduce the overarching methods I apply in the case studies, as well as the data collection process. Further details of particular methods will be provided in Chapters 4, 5 and 6.

Deliberative democratic theory has been applied in some empirical research areas rather than only staying as a set of theoretical debates; as argued by Chambers (2003), it has moved from the 'theoretical statement' stage into the 'working theory' stage. However, owing to the massive volume of data, the lack of widely agreed measurements, the difficulty of interacting with individuals online, and the complex ethical issues, the empirical study of online deliberation is challenging and needs more exploration. With these challenges, my thesis contributes to finding a possible way to explore online deliberation empirically. In Chapter 2 (See Section 2.4 Twitter), I discussed the deliberative potential of discussions on social media, particularly on the political issue of climate change, with evidence from the literature. Given the importance of Twitter for deliberation studies, I will answer the research questions by analysing empirical data collected from Twitter in Chapters 4, 5 and 6.

As a reminder, my research questions in this thesis are as follows.

> RQ1. How did the 'climate strike' protests affect the deliberative potential of climate change discussions on Twitter? This question forms the research question of Chapter 4.

RQ2. How did users collectively frame 'climate change' via hashtags? This question is the focus of Chapter 5.

RQ3. How did different user groups on Twitter collectively frame negative emissions via tweets? This question will be answered in Chapter 6.

To answer these questions, with my epistemological framework, I believe that the rise of social media brought more possibilities for researchers to use big data to explore user's behaviours, as 'large data sets offer a higher form of intelligence and knowledge that can generate insights there were previously impossible' (boyd and Crawford, 2012, p. 663). This chapter looks in detail at the underpinnings of my methodology. I start by looking in this chapter at the methodological literature focusing on online deliberation. A number of studies to date have sought to measure online deliberation, using a range of different measures and criteria. To classify these methodologies, Black and Burkhalter (2014) divided measures of deliberation into two types: '[t]hose that measure deliberation directly examine the deliberative discussion itself to determine the extent to which the discussion corresponds to theoretical conceptions of deliberation (direct measures)' (p. 327) and 'those that attempt to measure deliberation by studying variables that can be seen as indicators of deliberative processes (indirect measures)' (p. 324), which 'are often used when the antecedents or outcomes of the deliberation are the best (or only) data available to be measured' (p. 335). As I am measuring the deliberative potential of Twitter discussions directly according to theoretical conceptions of deliberation, this thesis uses direct measures. Within the direct measures, there is a range of different measures and methods. Discussion analysis is one of the direct measures, which is defined by Black and Burkhalter (2014) as the attempt to directly measure aspects of deliberation by systematically examining the communication during a deliberative meeting. Given that this definition does not reference any conversation online, for my purposes, it is necessary to broaden this definition to any formal or informal conversations online, such as discussions on Twitter around a certain political topic, rather than restricting it to deliberative meetings. Therefore, following Black and Burkhalter (2014), I define discussion analysis in my thesis as the attempt to directly measure aspects of deliberation by systematically examining the communication on Twitter around political issues. My thesis uses discussion analysis to examine the deliberative potential of discussions on Twitter about climate change and related topics.

To select explicit aspects of communication to measure, we can build our examination of direct measures following Lasswell's model of communication, 'one of the earliest and most influential communication models' (Shoemaker et al., 2003, p. 120), Lasswell (1948) proposed to describe the communication by looking at who said it (‘control analysis’), what was said (‘content analysis’), in what channel it was said (‘media analysis’), to whom it was said (‘audience analysis’), and the effects of the communication (‘effects analysis’). Among these five aspects, ‘control analysis’, ‘content analysis’ and ‘audience analysis’ look directly at the conversation itself. Although there are many critiques of this model (for example, it oversimplifies the complicated and dynamic communication process (Wilson, 2001)), it helps to classify the methodologies related to communication. Corresponding with Lasswell’s model, I found there are mainly two approaches in the literature to examine communication in online deliberation. One approach focuses on the content, i.e. what the participants said, and the other looks at interactions among participants (who said it to whom). Several researchers have also combined these two approaches together in single studies. In my thesis, I focus on ‘**who** said **what** to **whom**’, with different methods applied to explore different aspects of online deliberation. In particular, Chapter 4 investigates ‘who said it to whom’ using network analysis, Chapter 5 focuses on ‘what was said’ by studying hashtag co-occurrence network generated by the population who posted hashtags related to climate change, and Chapter 6 explores ‘who said what’ using structural topic modelling.

First, I will introduce how network analysis has been applied in the literature to study online deliberation.

3.2 Methodological background

There are two key components in social media studies: ‘what has been said’ and ‘who said it to whom’. Within this, those who study social media can fruitfully engage with either content-oriented studies, or network-oriented studies, or studies that combine the two. As introduced above, my thesis examines online deliberation by looking at ‘who said what to whom’ in discussions. In the sections below, I start with the introduction of network analysis, then focus on methods examining contents, and then the ones that combine both network analysis and content analysis.

3.2.1 Network analysis

A network refers to a set of entities connected by relations (also known as edges, ties or links), and a social network is a network in a social system (Contractor and Forbush, 2017). Network studies date back to the early 18th century, when the Swiss mathematician Leonhard Euler applied graph theory to substitute landmass and bridges with nodes and edges to solve the problem of traversal. In 1932, the Austrian-American psychiatrist Jacob Moreno developed the first graphic representation of social networks, which he called sociograms, in which nodes and edges represented individuals and the relationships between them (see Borgatti et al., 2009, and Contractor and Forbush, 2017, for more details of the history of social network analysis).

Concepts and techniques in network analysis have found wide application across many scientific disciplines, including business, communication, computer science, economics, education, marketing, public health, political science, psychology and sociology. For example, Fritsch and Kauffeld-Monz (2010) analysed information and knowledge transfer in 300 firms and research organisations involved in 16 German regional innovation networks. They found that strong ties between actors in regional innovation networks are more beneficial than weak ties for the exchange of knowledge and information. Mouttapa et al. (2004) examined whether social network variables, gender and ethnicity make differences to bullies, victims and aggressive victims using survey data collected from a sample of 1,368 primary school students.

In social networks, entities are often referred to as actors. Actors can be individuals or collective social units, such as organisations and nations. In Chapter 4, the actors are Twitter users, denoted by their usernames. Actors can also be non-human entities with which human actors may engage, such as movies, texts, research publications or hashtags (called ‘secondary actors’ by O’Neil and Ackland, 2018) discussed in Chapter 5 (See Section 5.2 Background). Networks can be analysed at the individual or group level, based on cross-sectional or longitudinal data, and compared between different populations.

Network analysis enables us to focus on the interactions among participants, which is different from the traditional way in communication studies, such as mass communication studies, which only focuses on the senders. Researchers in online deliberation studies who have used network analysis have been interested in the interactions between the sender and receiver, i.e. the structure of the discussion network generated by these interactions. ‘The intellectual premise of studying networks is that the relationships in which we are embedded emerge from, and contribute to, human behaviour and attitudes’ (Contractor and Forbush, 2017, p. 1).

Some research has turned to network analysis to measure deliberation. To examine the extent to which an online discussion approximates the ideal of deliberation (as discussed in Chapter 2), González-Bailón et al. (2010) collected data from the Slashdot forum, a discussion forum founded in 1997, and generated hierarchical networks by reconstructing the discussion threads, and classified the threads by the width (i.e. the maximum number of comments) and the depth (i.e. the number of layers) of the network. Their study found that online political discussion networks have a tendency to be broader and deeper than discussion networks of other topics, such as games and books. This study inspired me to study the deliberative potential of discussion networks of the political topic climate change on Twitter in a structural way. Shapiro and Park (2018) tested the deliberation potential in the post-video discussion network of climate change on YouTube. They calculated in-degree and out-degree centralities, transitivity and reciprocity, and confirmed that the discussions are elite-driven, which reveals that they are less likely to exhibit deliberation. The reciprocity of the discussion is crucial, because a discussion with participants responding to each other contributes more to deliberation than a discussion that only includes participants offering information (Hagemann, 2002). Uldam and Askanius (2013) pointed out that users commonly participate in online debate forums to demonstrate opinions in a unidirectional manner rather than to engage in dialogue (p. 1191). This damages the deliberative potential of online discussions, as there is little potential for users to develop their views if they do not engage with others. More deliberative public engagement techniques have been called for to 'break down entrenched camps and seek common societal goals in respect to this complex and morally uncertain issue' (Whitmarsh, 2011, p. 699). In Chapter 4 I will use reciprocity to measure online deliberation.

Milani et al. (2020) applied social network analysis to investigate how vaccine images are distributed on Twitter, and explored the influencers and potential gatekeepers of vaccination information. They compared the polarised networks formed by pro- and anti-vaccination users by analysing the size, density, and modularity of the networks, and they found that anti-vaccination users strengthen their relationships by frequently retweeting each other, while pro-vaccine users form a fragmented network by strategic connections. Mascaro et al. (2012a) integrated social network analysis with communication theory to study the conversation networks generated by ten discussions on the Tea Party Patriots Facebook page, with 926 direct addresses identified from 529 individuals. Pairs of participants were used to construct a weighted and directed network for the ten parent posts and a more extensive network including all the participants in those ten posts. They analysed the betweenness, in-degree and out-degree of the networks to identify the behaviour of dissenters. Mascaro et al. (2012b) also did another study about the weighted social networks of discourse, across three units of analysis: time, parent post category and specific parent posts, taking the Coffee Party Facebook group administrator account as a case study. Their study found different features of the network structure, centralisation and leadership in different periods, and found the agenda-setting and contributing role of the Coffee Party administrators. It also revealed that the participants changed their roles in different parent posts and categories.

As mentioned above, network analysis enables us to focus on participants and the relationships among them and track the structural and dynamic changes of the discussion. Taking these advantages, I will apply network analysis in Chapter 4 to examine the deliberative potential of climate change discussion on Twitter by studying the participants' conversational interaction and the structural changes of the discussion networks.

3.2.2 Methods focusing on content

Apart from the structural way to examine online discussions, a range of different techniques has been applied to examine content on social media, both quantitatively and qualitatively. Text-based research methods analyse documents' thematic and semantic content (Krippendorff, 2019). Content analysis, defined as 'a systematic, replicable technique for compressing many words of text into fewer content categories based on explicit rules of coding' (Stemler, 2000, p. 1), is the most common analytic method among various approaches to studying how people communicate on social media (Snelson, 2016). Similarly, content analysis is also commonly applied in online deliberation studies. Some studies applied content analysis using the manual coding method. For example, Wilhelm (1998) used content analysis to examine how deliberative an online political discussion is through three topics: (1) the exchange of information among forum members, (2) the exchange of opinions and the incorporation of others' viewpoints, and (3) the in-group homogeneity of political opinion on Usenet newsgroups (Wilhelm, 1998, pp. 319–321). Friess et al. (2020) applied content analysis to code the rationality, constructiveness, politeness, civility and reciprocity of comments on Facebook to measure the deliberative quality of online discussion.

Some studies, for example semantic network analysis, have also applied other methods to analyse content. Semantic network analysis is also a network analysis method, defined as 'network analysis using written texts to identify salient words and concepts in order to extract underlying meanings and frames from the structure of concept networks' (Shim et al., 2015, p. 58). I introduce it here rather than in the network analysis section because it focuses on content. Yang and González-Bailón (2018) reviewed semantic network analysis and how it has been applied in public opinion research. Rather than social actors and their social relationships, nodes in semantic networks are semantic concepts, such as places and values, and ties are associations between these concepts, such as co-occurrence. Featherstone et al. (2020) applied semantic network analysis to identify public opinions on childhood vaccination themes on Twitter, and found that HPV vaccination as a disease preventative was the most prominent theme. Eddington (2018) constructed hashtag semantic networks by separating the text corpus of tweets into co-occurring pairs for hashtags, and by taking hashtags as nodes and the co-occurrence of hashtags as edges. Eddington's work is significant. However, as shown in the definition of semantic network analysis above, it analyses 'concept networks', while hashtags are not equal to concepts, strictly speaking. Therefore, instead of using semantic network analysis, in Chapter 5 I apply network analysis to analyse hashtag co-occurrence networks, treating hashtags as nodes and their co-occurring relationships as edges or ties.

The widely applied approaches to analysing content are typically conducted in a manual way. However, reliance on the manual coding approach has two major limitations, according to Lesnikowski et al. (2019). First, manual techniques are hard to apply to large comparative analyses, especially with 'big data' sources from social media. Second, because of differences in understanding the concepts, especially when it comes to controversial topics across places and sectors such as climate change, it is challenging to rely on predetermined conceptual categories used in manual content analysis.

Some researchers have proposed some other ways in computer science to study online deliberation from the perspective of content, such as topic modelling (Shim et al., 2015), corpus analysis (Collins and Nerlich, 2015), etc. Topic models are powerful tools to analyse the connections among words based on probability, which helps to examine large corpora (Ramage et al., 2009). Among different topic models, latent Dirichlet allocation (as known as LDA) is a widely used unsupervised machine learning technique that identifies latent topic information in large document collections (Vayansky and Kumar, 2020). Shim et al. (2015) proposed applying topic modelling as a method for frame analysis. Structural topic modelling (STM) is differentiated from other topic modelling methods, with extensions that facilitate the inclusion of document-level metadata, for example the stance of speakers and timestamps of comments (Roberts et al., 2014). Apart from identifying topics, STM enables us to study the context in which the topics appears at different frequencies (Stelmach and Boudet, 2021). To study the frames related to negative emissions (NE) that different user groups generated, I will apply STM in Chapter 6.

3.2.3 Network and content

The above approaches examining the structure of discussion networks and content do not stand separately from each other. According to Monge and Contractor (2003), both the structure of the communication network and its contents are essential for communication studies. Deliberation is a component of wider communication. Similarly, the structure of the network and contents are two important components of deliberation studies, as we not only need to know how people are participating in the discussions deliberatively but also need to examine what they are talking about in this process. While many have studied these aspects in isolation, as mentioned in Section 3.2.1 and Section 3.2.2 above, a growing number of researchers are arguing that they should be studied in parallel.

Some researchers have already combined the two approaches to examine online deliberation. For example, Farrell (2015) applied both network analysis and computational text analysis to analyse the structure of the climate change counter-movement and its impacts on the news media and politics. Hagemann (2002) applied content analysis of two political discussion lists from the Netherlands to measure what he called ‘deliberativeness’, and found that both lists had only a few active participants engaged in the discussions, and there was rarely any argumentation in their opinions. He also applied network analysis when analysing the structure of discussions between participants when posting to the lists. He operationalised the reciprocity in three ways: (1) comparing the number of responses with the number of seeds and stand-alone postings, (2) counting explicit ‘agrees’ or ‘disagrees’, and (3) counting the interruption of the discussion. We can find that these three ways are specifically designed to fit the features of discussion lists, which inspired to me find my way to measure reciprocity in Chapter 4. Black et al. (2008) combined content analysis with social network analysis to examine the deliberative policymaking process on Wikipedia, ‘when members of the Wikipedia community propose, discuss, agree on, and enforce the policies that guide all their interactions’ (p. 1). Each post analysed was coded to eight aspects of deliberation: ‘creating information base, prioritising values, identifying solutions, weighing solutions, making decisions, comprehension, consideration, and respect’ (p. 10), and the results revealed that the discussions are good in problem analysis and information provided, but ‘mixed in the group’s demonstration of respect, consideration, and mutual comprehension’. Network analysis was used to study the interaction structure of the discussion thread, which helps to understand the equality and the influence of the participants in the discussion. Researchers have pointed out the tendency for several users to monopolise online discussion (e.g. Jankowski and van Selm, 2000), which is harmful to deliberation. However, there are some limitations in their measure of equality. For example, taking the degree centrality as the size of participants’ influence in the discussion oversimplified the problem. Kim and Park (2012) applied Leydesdorff’s (2003) triple helix indicators model, which has been used to ‘define the primary institutions in knowledge-based societies universities, academia, and governments’ (p. 124), to political communication, looking at how five prominent South Korean politicians from four political parties used Twitter as a tool for political deliberation and participation. They took ‘reciprocity’ as a measure of the frequency of Twitter being used as ‘a direct communication channel between politicians and their followers'. This operation of reciprocity fits their research purpose well because they studied the communication between two unequal social roles (politicians and the public). Chapter 4 looks into the communication among the population without differentiating between the participants, so I operationalise reciprocity as how often the participants reply in the discussion. Kim and Park (2012) also examined political deliberation by looking at whether a small number of users dominated the Twitter discussion to measure the level of balance in the communication system. I regard the level of balance as equality that will be measured by the Gini coefficient, a standard inequality measure for income and wealth distributions, which will be introduced in Chapter 4.

Cinalli and O'Flynn (2014) applied network analysis and 'claim-making analysis' with deliberative theory to test whether public deliberation contributes to political integration and features of the relationship, taking the political integration of Muslims in the ethnic relations of Britain as a case study, using data from two British newspapers, *The Guardian* and *The Times*, in 2007. The three basic requirements of the public deliberation were summarised as 'actors (i) couch their interventions in language that is acceptable to others, (ii) provide a valid supporting argument and (iii) show concern for the general interest' (p. 431). To operationalise these requirements in the case study, the authors took 'claim-making analysis', a qualitative method based on Koopmans and Statham (1999) and Giugni and Passy (2004), to code the 'deliberative intervention', defined as 'a verbal statement made by an actor in the public sphere that rests upon a variable articulation of an argument in relation to the argument of another actor' (p. 434). Three techniques in network analysis were then applied to analyse actors' positions and the overall structure of the field: density, centrality and cliques ('blocks of actors that stand out within the larger network for the fact that they have all forged mutual ties with one another' (p. 436)). Density is used to measure the degree of political integration in the field, in-degree and out-degree centralities are used to measure the actor's 'relevance' and 'activism', and cliques are used to identify the entrenched blocks, which can be an indicator of polarisation. I take density as a baseline for other measures in Chapter 4, as it shows how active a discussion network is in general.

Several scholars have attempted to measure political orientations quantitatively. Applying the 'Intelligent Cyber Argumentation System's (ICAS) cognitive computing component', a tool developed by Liu et al. (2010), Sirrianni et al. (2018) tried to measure polarisation quantitatively in online argumentation, with the assumption that measuring polarisation reflects whether online deliberation captures collective intelligence and crowd wisdom. Some studies have also assessed the deliberative potential of social media through testing the political homophily, with the assumption that ‘homophily produces shared political attitudes which can result in political polarisation’ (Colleoni et al., 2014, p. 319), which in turn impedes deliberation. For example, Colleoni et al. (2014) combined machine learning (supervised classification) and social network analysis to classify Twitter users as Democrats or as Republicans according to the political orientation in the content shared, and found that the structures of political homophily are different from each other. Although this paper is significant when considering the enormous data size (467 million tweets from 20 million users), in my view the way it classifies Democrats and Republicans is too simplified. In the machine learning process, the training set is ‘obtained by scraping all the political tweets of the users that follow Democrat or Republican accounts, assuming that they share the same political attitude of the accounts they follow’. This assumption lacks full consideration, as users following a Democrat or Republican account are not necessarily themselves Democrats or Republicans. This is a limitation of the content analysis using machine learning or, more generally, the big data techniques. Despite the limitations of machine learning, in Chapter 6 I apply STM, a supervised machine learning method, to analyse the content of tweets.

Jackson and Foucault Welles (2015) took a more multimethodological approach, combining network analysis and focused discourse analysis to analyse the discussion network of #myNYPD on Twitter, and discourse analysis of the coverage of the hashtag on mainstream media to process the hashtag’s collective hijacking. The network generated in their study consists of users connected by mentions and retweets. Jackson and Foucault Welles (2016) combined network analysis with discourse analysis again to analyse the #Ferguson Twitter network to identify online dissent and story framing of an emergent counter-public. But this time they took the dynamics into account by analysing seven networks at seven timepoints and took the results of these networks together with the aggregate network as the longitudinal discovery. Though ‘capturing time remains a challenge in network research’ (Ryan and D’Angelo, 2018, p. 150), according to Snijders (2005), ‘the idea of regarding the dynamics of social phenomena as being the result of a continuous time-process, even though observations are made at discrete time points, was already proposed by Coleman (1961)’ (p. 216). Though it is challenging to analyse the longitudinal process in this thesis, I will take important events as cutting points to compare the networks before and after the events in Chapter 4 (climate strikes) and Chapter 5 (COP24, a conference).

Besides the criteria mentioned in the above studies, i.e. rationality, civility, equality, reciprocity, density, centrality, cliques and so on, Schneider (1997) measured diversity by the number of days featuring messages outside the normal bounds of activity and the presence of multiple conversational patterns within threads of messages. Collins and Nerlich (2015) measured online deliberation through ‘topicality’, utilising semantic annotation to identify key themes, ‘argumentation’, focusing on incivility, questions, and alternative viewpoints, as well as ‘reciprocity’, looking at the use of specific usernames in the discussion.

As argued by Cinalli and O’Flynn (2014), although public deliberation can be defined in terms of several basic requirements, we need to pay attention to the context to which these requirements are applied when operationalising in empirical analysis. In addition to the context, it is also worth noting that, as argued by Black and Burkhalter (2014), ‘because the conceptual foundation of democratic deliberation is fundamentally normative, it is difficult to precisely determine a threshold level that variables must meet in order for group discussion to count as being deliberative’. Instead of determining a threshold level that measures whether a discussion counts as deliberative or not, I propose to measure how the deliberative potential changes. In Chapter 4, I first propose focusing on the structure of participants’ interactions in the discussions in a structural way. To successfully understand online deliberation, we can study a range of measures in network analysis, as mentioned in the literature above. I take reciprocity, equality and diversity as the criteria of deliberation in climate change discussion networks, which are respectively operationalised in Chapter 4 as the mutuality of networks, the Gini coefficient of the degree distribution, and the mean of unique users in the network. I aim to examine the extent to which the climate strike movements change different aspects of deliberation.

My thesis examines online deliberation both from the structure of discussion networks and from the content the participants generated. When examining the content, I look not only at the structure of how they constructed the content via hashtag co-occurrence networks (Chapter 5), but also at what different user groups said (Chapter 6). All these methods enable me to study online deliberation more comprehensively and systematically. In the following part, I introduce the general data collection process of the three case studies.

3.3 Data collection

3.3.1 Big data collection

The massive growth in data with the rapid development of information technology gave birth to the term ‘big data’ in the early 1990s. Big data has been characterised in terms of properties starting with the English letter V, such as volume, velocity, variety, veracity and value (Tripathy et al., 2018). Here volume points to the massive amount of data that can be produced; velocity means the rapid generation of data; variety stands for different types of data, such as images, text and videos; veracity represents the accuracy of the data; and value stands for the real values of the data (Bazzaz Abkenar et al., 2021). Big data ‘offers the possibility of shifting from data-scarce to data-rich studies; static snapshots to dynamic unfoldings; coarse aggregations to high resolutions; relatively simple hypotheses and models to more complex, sophisticated simulations and theories’ (Kitchin, 2013; p. 263). All the five features (the five Vs mentioned above) are available on social media, so a vital application of big data is in the field of social media studies. Importantly for researchers, user-generated content on social media, such as blogs, tweets and interactions on social media, can be regarded as a key form of sociological big data (Kitchin, 2014). ‘Big social data’ (Manovich, 2012), offered by social media’s application programming interfaces (API), provides us with a way to trace individual users’ public communicative interactions (Bruns and Highfield, 2015). The new scale and forms of data have brought changes in data collection and analysis.

There are two typical ways to collect data for social media studies. The first is offline approaches, such as interviews, surveys, and focus groups, commonly used to examine users’ behaviours or experiences with social media. For example, Fox et al. (2013) conducted ten mixed-sex focus groups to investigate the role of Facebook in romantic relationships. Still, as the authors mentioned, the limitation of this approach is that, ‘although focus groups can offer deep insights into several issues, the commonality of these beliefs across broader populations is unknown’ (p. 789). Essentially, it is hard to collect larger datasets using offline approaches due to the limited budget and time.

Taking the benefit of big data, the second way is online approaches, which collect content and affordances using computational techniques, typically through APIs. This way has been widely used. For example, Shugars and Beauchamp (2019) collected 63,671 unique tweets with the keyword ‘Trump’ to develop a model of argument engagement. Compared to other methods, this way enables researchers to access a massive amount of data, cover a much larger population, and access different forms of data sources, such as image, video, text and share numbers. Bruns (2015) indicates that data collection from APIs can prevent influencing users while observing, as users are unaware of researchers and their communicative behaviours are not changed by the data collection process (Bruns and Highfield, 2015).

Given the foci of my research are the conversations and content users generated on Twitter, I conducted the online approach, i.e. collecting data from Twitter without engaging the users offline.

3.3.2 Challenges in big data collection

However, while social media, such as Twitter, offers many opportunities, it also poses challenges for social science research. The first challenge is how we should use social media data for research while obeying ethics requirements, which is still an open question. Besides the usual ethical issues associated with research involving human participants, social media studies are more ethically questionable (D'Angelo et al., 2021), as Kadushin (2005) has noted that 'the collection of names of either individuals or social units is not incidental to the research but its very point' (p. 141). Many researchers, such as Hunter et al. (2018), have noted that social media studies remain an ethically interesting area because of data privacy, anonymity, confidentiality, authenticity and the rapidly changing global environment. Ongoing debates exist when it comes to ethical issues of social media studies, and as stated by Beninger (2016), it is ideal to follow 'a rigid set of rules for regulating what ethical considerations to make throughout a study', but 'doing research ethically is not about finding a set of rules to follow, nor is it about completing a checklist. Rather, researchers need to work through a set of context-specific decisions on a case-by-case basis and be guided by core ethical principles' (p. 8). My research is guided by this principle. As users had agreed to the terms and conditions of Twitter before they started to use the platform, which include providing others with their public data, and I collect part of this public data through Twitter API following the developer's policies and agreements, this can be taken as an indirect way of obtaining informed consent from the users. As I analyse the content collectively, I do not reveal who said what at the individual level but the group level and the overall level. What's more, I keep the data anonymous throughout my thesis, except the names of several celebrities (i.e., Greta Thunberg and Donald Trump), to mitigate potential harms. The data collection of this thesis has received ethical approval from the Australian National University with Human Ethics Protocol ID 2019/325.

The second challenge is the noise. For example, the character limit on tweets often means users abbreviate words (e.g. 'QOTD' for 'quote of the day', 'BTW' for 'by the way'). Users also use sarcasm and humour on Twitter; as stated by Ravi and Ravi (2015), '[a]mbiguity and vagueness have been considered major issues since user reviews are often written using a loose style than standard texts, and often express sarcasm (mock or convey … irony), rhetoric or metaphor' (p. 23). This kind of ambiguity and vagueness is 'a significant issue for automated techniques and the accurate assessment of creative language use' (Sykora et al., 2020, p. 2). Another well-known problem is non-human conversationalists, known as social bots (Ferrara et al., 2016), which are hard to detect. This is not a significant problem in my research because

I am studying social media as it is, and bots form a part of social media. Users do not identify social bots first before they read and understand the content, so it was not necessary in my data collection process to distinguish and remove content generated by social bots.

Other challenges include ‘how to understand online behaviour, and how to apply traditional social scientific concepts of sampling and inference, and coding and interpretation to understand the relationship between online communities and the wider population’ (Sloan and Quan-Haase, 2017, p. 5). Despite these challenges, there has been a noticeable growth in social media studies regarding different topics. Social media content, such as Facebook posts, tweets, YouTube videos and comments, and their affordances, such as links and share numbers, have been collected as a data source. For example, Mihelj et al. (2011) used content analysis to investigate the potential of video activism on YouTube for the civic culture in climate justice, through a case study of online debates (by YouTube comments) stimulated by a video that called for a protest against the 15th United Nations Climate Change Conference. Their results show that the commenting practices on YouTube did facilitate conversation between otherwise disparate publics. However, the potential of YouTube for deliberation is ‘significantly impeded by security issues. Notably, climate justice activists are aware that the use of online spaces for organization and debate can pose threats to their safety’ (p. 1200). Besides, ‘the commenting practices on YouTube further impede the emergence of civic cultures because comments frequently are characterized by hostility and do not invite dialogue’ (p. 1200). Vu et al. (2021) explored NGOs’ framing of climate change by analysing Facebook posts of 289 global climate NGOs from 18 countries.

Others have used mixed methods. For example, Bloomfield and Tillery (2019) selected two Facebook groups to investigate the roles that the Internet and social media played in distributing climate change denial information. In particular, they first looked into ‘the external communication of the groups, how they link to other sites, and how they establish themselves in a network of supportive and competing scientific messages’, and then focused on ‘the internal communication on the Facebook pages’ (p. 26). They employed topic analysis to analyse the rhetorical strategies, and applied actor–network theory to analyse the networking strategies by considering the links and other affordances in the climate change information network. Their analysis shows that hyperlinks and blogging harmfully enable the repeated misrepresentation of peer-reviewed scientific research to fit the narratives of climate change hoax, and the Facebook pages as echo chambers can lead to an extremist community.

This thesis used hashtags and keywords to collect data about climate change from Twitter API. In the following two sections, I will specifically introduce the details.

3.3.3 Data collection in Chapter 4 and Chapter 5

Among the massive quantities of information provided on Twitter, hashtags have been used as a way for people to gather and discuss specific topics. Hashtags, denoting any characters following a '#' symbol in tweets, are a 'community-driven convention', which gained ground in 2007 during the San Diego forest fires (Small, 2011). Hashtags can promote the circulation of specific topics and help users gather around common interests or activities, because users can start a discussion with a hashtag, and others can join the conversation using tweets that include that hashtag without following relationships with others (Bruns and Highfield, 2015). The 'technological affordance' of hashtags enables many users to participate in mass discussions on Twitter at once (Eddington, 2018), which in return provides a critical dataset for researchers.

Taking this advantage, for Chapter 4 and Chapter 5 I collected tweets that contained the hashtag #climatechange from Twitter using NodeXL Pro, an add-in for Microsoft Excel that collects data through Twitter API (Smith et al., 2010). The dataset covers the period 10 September 2018 to 10 September 2019. Collected alongside the content of tweets are the conversational relationships, which are denoted with the character '@' and a user's name, the user's tweet statistics (i.e. the number of times the tweet has been retweeted, favourited and replied), and the bio-information of users engaged (e.g. locations and preferences shown in their descriptions). Only tweets in English were kept for the analysis in my thesis. Hornsey et al. (2018) pointed out that the impacts of conspiratorial and conservative ideologies on climate change scepticism are mainly based on data collected in the US, which cannot show the worldwide phenomenon. However, my data is collected from the international platform Twitter, which can show a more international picture, although most Twitter users in my dataset are from anglophone countries.

It should be noted here that it is impossible to collect all the information on Twitter due to the restrictions of the standard Twitter API; for example, we cannot retrieve data that was generated more than seven days beforehand, and it only returns about 1% of all tweets in real time randomly (https://developer.twitter.com/en/docs/twitter-api/tweets/sampled-stream/api-reference/get-tweets-sample-stream). To collect as much information as possible, I conducted the collection regularly (every four days), merged the separately collected Excel files, and removed the duplicates (typically tweets collected twice due to an oversampling process) using

R programming. The regular collections caught the pattern of the data in the long run. In other words, because the collections were conducted regularly throughout over one year, the differences between weeks or months show the pattern of the topic. It is worth noting that the time of day of data collection might lead to a higher prevalence of Australian participants.

The above dataset I introduced is the complete dataset for Chapter 4 and Chapter 5, but the two chapters use different parts.

In Chapter 4, I analyse the impacts of the discussion of climate strikes on the topic of climate change, by examining the changes of equality, reciprocity and diversity of the discussion networks, constructed by replies and mentions. There are four main ways that people connect with each other on Twitter: retweeting, following, replying and mentioning. Retweets are similar to forwarding emails, which are often used in the study of diffusion of information. A reply is a response to another user's tweet that begins with the @username of the person they are replying to, and a mention is a tweet that contains @username anywhere other than at the very start. Replies and mentions are possibly reflecting what users write on Twitter, compared with following; it is quite possible that you would follow someone without ever trying to directly communicate with them. For example, I might follow the prime minister of Australia on Twitter without ever being in any communication with him. Among these four kinds of relationships, replies and mentions directly reflect the conversational aspect. In my dataset, if user A replies to or mention user B, there is a tie between A and B in the network.

In Chapter 5, I extract the hashtags and their co-occurring relationships from the dataset and analyse the hashtag co-occurrence networks.

3.3.4 Data collection in Chapter 6

As Chapter 6 takes a subtopic of climate change, negative emissions (NE), as the case study, the data collection is slightly different from the previous two chapters. The data in this chapter was collected through Twitter API as well, but I used keywords rather than hashtags to collect tweets talking about NE, because the topic is not as well known as climate change. NE is a rather new topic, which has mainly been talked about by scholars in science, and, even among these scholars, different terms have been used to talk about the same or similar topic. Therefore, the first step was to cover the terms that have been used to talk about NE before deciding which keywords to use. Before the data collection, I built up a list of terms relating to NE through a survey to assist with data collection. The survey was administered to 48 authors who had published academic articles on NE, from whom 13 responses were received. The authors were asked what other words or terms come to mind when explaining or discussing NE. Based on their responses, the search terms I used to collect Twitter data were: 'CO2 removal', 'greenhouse gas removal', 'carbon sequestration', 'CO2 sequestration', 'carbon management', 'carbon drawdown', 'carbon capture', 'CO2 capture', 'blue carbon' and 'negative emissions'. As I focus on original content posted by users, retweets and replies have been excluded.

This thesis focuses on tweets in English, because 'it is used in enough different countries to give a useful sample' (Wilkinson and Thelwall, 2012, p. 1635). Thus, the politics of the climate change discussion in this thesis is pan-Anglo politics.

After extracting tweets in English, there were 6,182 Twitter users, who posted 8,524 tweets related to NE in the time frame from 10 June to 10 September 2019 (93 days).

From the next chapter, I will introduce the details of methods and data collection in each case study in detail.

Chapter 4 Impacts of Climate Strikes on the Deliberative Potential of Climate Change Discussions on Twitter: A Structural Examination of Discussion Networks

4.1 Introduction

The last two decades have seen a massive expansion of online discussions via social media and a related rapid emergence of environmental movements on a global scale. As defined by Castells (2015), a networked social movement is a loosely organised campaign relying on networked communication technologies, such as Twitter, and personal networks to achieve goals. As a new way for the public to achieve goals in political issues, how networked social movements engage in deliberation is worth investigating. The climate strikes are one of the most widely known climate change-related networked social movements of recent years. They are also called ‘school strikes for climate’ or ‘Fridays for future’. Led by the Swedish (then) school student Greta Thunberg, ‘school strikes for climate’ have been attracting attention since 2018, inspiring worldwide environmental movements. But less is known about how these networked social movements impact online discussions on a broader scale. For example, how did the climate strikes impact the deliberative potential of climate change discussions online? More specifically, what measurable changes did users discussing climate strikes bring to deliberation in climate change discussions on Twitter? This chapter seeks to answer this question by measuring the structural changes of the discussion networks using social network analysis. To do this, in this chapter I adapt Schneider’s (1997) framework of four dimensions (reciprocity, equality, diversity and quality) of the ideal public sphere, and test the changes of reciprocity, equality and diversity of discussion networks that climate strikes brought to climate change on Twitter using social network analysis with operationalised measures.

The first contribution of this research is to sketch the structural features of online discussions by applying social network analysis. This is a new but valuable contribution for scholars in climate change studies, as online communication has been an important part of modern life and impacts people’s behaviours, but less research has focused on the structural features of the discussion networks about climate change online. Second, this chapter applies the criteria for assessing online deliberation to test the deliberative potential of online discussions, which can potentially provide an operationalised way to examine how deliberative other online topics might be. Third, this chapter analyses the changes brought by users discussing social movements to deliberation in broader political issues, which in this case is climate change. Fourth, it is an innovation to apply the Gini coefficient and the Lorenz curve in measuring deliberation in this chapter. Specifically, the chapter quantifies equality in online discussion networks by calculating and representing the degree distribution statistically and visually using the Gini coefficient and the Lorenz curve, which have been applied to measure inequality for income and wealth distributions.

This chapter begins with a review of the literature on online deliberation and climate change, and the operationalisation of the measurements of deliberation. In the methods, after introducing climate strikes and the data, I analyse the differences in deliberation before and after the discussion of climate strikes became prominent, from three dimensions: reciprocity, equality and diversity. I then present the results and a discussion of the findings.

4.2 Background

4.2.1 Online deliberation and climate change

Deliberation is difficult to achieve, but it brings considerable benefits in transforming the public response to climate change and, potentially, the nature of politics itself (Niemeyer, 2013). Rather than consensus, democratic deliberation is best understood as being oriented towards mutual understanding, which means that people are motivated to resolve conflicts by structured argument (Warren, 1996). Even though citizens tend to have a similar set of capabilities before and after deliberation, without fundamental changes (Barabas, 2004), and they likely keep a similar value set as well, some values, such as those related to the environment, will have been activated in the process (Niemeyer, 2014). Through deliberation, citizens can be attuned to environmental complexities and reflect on the issue with a long-term view (Niemeyer, 2014), which helps to collectively tackle the climate problem.

Even though there have been debates about what social media brought to deliberation, as discussed in Chapter 2, this thesis takes a positive perspective on social media's role in deliberation, given that one important aspect of the democratic promise of online discussions is that individuals can actively generate, circulate and evaluate ideas. There are more pieces of evidence when it comes to climate change, as Talpin and Wojcik (2010) argued: 'both online and face-to-face deliberation definitely have a learning impact on actors, a vast majority of participants declaring that they had learned about climate change, other related issues, or the way to express their opinions' (p. 86). As noted in Chapter 2, I define online deliberation in this thesis as the **informal online discursive process in which participants express their opinions and discuss with each other with the potential goal of achieving mutual and**

collective understanding about political issues. In this chapter, I focus on the informal discussion of climate change among Twitter users.

Social movements are defined as loose networks of organisations and individuals with common values participating in politics using unconventional forms to reach political goals (della Porta and Diani, 2006). According to Doerr and della Porta (2018), '[p]rogressive social movements nurture conceptions of deliberative democracy' (p. 12), and 'activists in different generations and regions have developed and combined different practices of participatory, deliberative, and radical democracy that have consensus-oriented decision-making, inclusivity, equality, and transparency at their heart' (p. 4). For example, Doerr (2008) found that, under conditions of extreme resource inequality and ideological heterogeneity, activists can contribute to deliberation by setting up multilingual and culturally diverse spaces in the context of the World Social Forum. However, besides this positive attitude to the role of social movements for deliberation, scholars in deliberation studies have also expressed their concerns about the lack of openness to other political actors' ideas in social movements, and about activists' use of social movements to promote their certain political goals, both of which hinder deliberation (Talisse, 2005). In this chapter, I examine how social movements change the deliberative potential of online discussions. Specifically, I focus on the changes that climate strikes brought to the discussion of climate change on Twitter.

On 20 August 2018, the Swedish climate activist Greta Thunberg, then in the ninth grade, decided to not attend school until the 2018 Sweden general election on 9 September after heatwaves and wildfires in Sweden, thus starting the first ever school strike for climate ('skolstrejk för klimatet') and laying the kernel for what would become a global social movement. Strikes began to be organised around the world, inspired by Thunberg, starting in November 2018 (John, 2019). Thousands of schoolchildren soon followed Thunberg, demonstrating in cities all around the world under banners such as 'Fridays for Future', 'School Strike 4 Climate' and 'There's No Planet B'. According to the organisers, the global climate strike started on 15 March 2019 in 125 countries with 1.6 million participants (Wahlström et al., 2019) (for detailed records, see Figure 4-1). These records only count offline participants. But there were a huge number of online participants on Twitter attending the movements discursively.

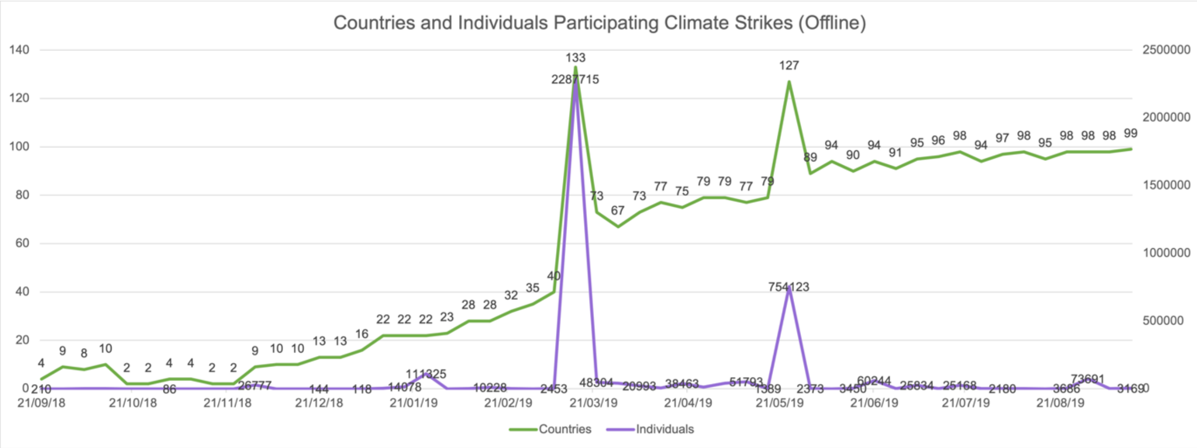

Figure 4-1. International growth in climate strikes by number of countries (LHS axis) and number of individuals (RHS axis) participating offline

Source: Fridays for Future, https://fridaysforfuture.org/what-we-do/strike-statistics/list-of-countries.

Social media played a crucial role in engaging people worldwide in the strikes (Boulianne et al., 2020). As one of the main communication tools of climate strikes, as Haßler et al. (2021) stated, Twitter is useful for the movement because many of the participants in the movement were active users of Twitter. But did climate strikes change the nature of the deliberative potential of climate change discussions on Twitter? If so, how? Before answering this question, I will test whether climate strikes raised the visibility on Twitter of the issue of climate change first, which would contribute to engaging more diverse users to attend the discussions, or vice versa (Hypothesis 1). Based on the discussion in Chapter 2 and the section above, I hypothesise that climate strikes brought positive impacts on the deliberative potential of climate change discussion on Twitter (Hypothesis 2).

> Hypothesis 1. Climate strikes raised the visibility on Twitter of the issue of climate change.
>
> Hypothesis 2. Climate strikes increased the deliberative potential of climate change discussion networks on Twitter.

4.2.2 Measurements of deliberative potential

Not all discussions are deliberative. Despite the debates about the role of online political discussion in democracy, as introduced in Chapter 2, there is no agreement on how to measure the extent to which online discussions are deliberative. Scholars of deliberation agree that deliberation is a demanding type of communication that has to follow certain rules, and they have developed different models from various perspectives to construct empirically grounded studies of deliberation. Even if the exact rules are a matter of dispute, as stated in

Chapter 2, there is a consensus that deliberation is a rational, interactive and respectful form of communication (Bächtiger and Pedrini, 2010). To understand the deliberation of online political practices, online discussions should be 'assessed as discursive actions that hint towards the possible existence of a public sphere' (Del Valle et al., 2020, p. 1). This view also shows how scholars are inspired to measure deliberation through dimensions of the idealised public sphere, such as Schneider (1997) and González-Bailón et al. (2010). The public sphere is defined as 'the social sphere constituted of rational-critical discourse that enables the formation of public opinion' (Dahlberg, 2001).

There are scholars who have measured the state of deliberation in online political discussions directly. For example, Collins and Nerlich (2015) examined deliberation in user comment threads responding to climate change-related articles on *The Guardian* through reciprocity, topicality and argumentation, focusing on questions, incivility and alternative viewpoints. Del Valle et al. (2020) proposed a coding manual to assess the deliberation in Twitter political discussions, based on the integration of the ideal deliberation in public sphere theories, the so-called rational–critical debate, with these research questions: '[t]o what extent are elements of the rational-critical debate present in the communications of Dutch MPs on Twitter? And thus, to what extent do these communications display elements of the ideal Public Sphere?' (p. 2). Del Valle et al. (2020) adapted the coding manual proposed by Borge Bravo and Santamarina Sáez (2016) and Bravo et al. (2019) to a Twitter sample, and proposed a coding manual of tweet text that includes various aspects such as communication strategy, mentions, questions, external justification, internal justification, reflection, empathy and plurality, and found that the discussion should not be considered 'full-fledged' deliberative. However, such depth is not feasible enough for a larger dataset. Besides this approach focusing more on the content of discussions, there are also researchers focusing on the structural features of the discussions. For example, González-Bailón et al. (2010) constructed the discussion threads on the Slashdot forum as hierarchical networks and proposed a model for analysing online deliberation. Based on two features of deliberation – 'the extent of representation and the intensity of argumentation' (p. 232) – they built a framework using the width and depth of the interactions for comparative analysis of deliberation between online forums, which is less explored in the literature. As they stated,

> Rather than looking into the content of the discussions, or assess the nature of the arguments exchanged, we propose focusing on the structure of the interactions in which discussants participate. Our aim is to identify the network features that set the necessary (albeit not sufficient) conditions to reach the ideal of deliberation, and ultimately test how close to that ideal discussion networks are when formed in different online settings. (p. 233)

I follow this logic in this chapter to measure the deliberative potential through structural features of the discussion network rather than focusing on the content. Instead of comparing between different topics or a different platform, in this chapter I compare the criteria between the networks before and after an event occurred. However, their model is more suitable for hierarchical thread networks, rather than the reply network that I will construct in this chapter. I follow the framework proposed by Schneider (1997) instead. Based on Habermas's *Structural Transformation of the Public Sphere*, Schneider (1997) proposed four dimensions of the idealised public sphere – equality, reciprocity, diversity and quality – and provided specific measures for each dimension applied to the online discussion of abortion in a Usenet newsgroup. Because it is harder to measure quality using social media data, especially snippets of text on Twitter, this chapter will not analyse the quality.

In sum, this chapter operationalises the measurement of deliberation from three dimensions – reciprocity, equality and diversity, which will be introduced below.

4.2.2.1 Reciprocity

Reciprocity refers to the opportunities to gain knowledge of others' perspectives, and the degree to which these opportunities are realised in deliberation (Schneider, 1997). In the idealised public sphere, reciprocity would be maximised: that is, each actor would establish a reciprocal relationship with every other actor. Reciprocity is an important consideration in assessing deliberation because it indicates the degree to which participants are actually interacting with each other and working on identifying their own interests with those of the group, as opposed to talking past each other or engaging in simple bargaining or advocacy (Wilhelm, 1998).

Vertices or nodes are social actors or objects in a network. An edge or a link describes the relationship between vertices and is drawn as a line linking two vertices. Reciprocity in social network analysis is defined as the likelihood of vertices in a directed network to be mutually linked. With higher reciprocity, it is more likely that the actors who receive replies from others in a discussion network will themselves reply. With Twitter data, there are four possible dyadic relationships in the discussion network that help us to understand how relationships between two users are structured: (1) A and B do not talk to each other, (2) A replies to B but B does not reply to A, (3) B replies to A but A does not reply to B, and (4) A and B reply to each other. The relationship between two users can be considered reciprocal if they exchange replies, i.e. the fourth case mentioned. (It is worth noting that the types here are categorical. For example, if A replied to B 100 times and C replied to B once, both A and C have reciprocal relationships with B in the discussion network. A different form of analysis might further delineate categories here.) However, some scholars have found that there are serious threats to user replies generating deliberation on social media. For example, as Uldam and Askanius noted, '[o]pportunities for user participation in online debate forums are most commonly used to demonstrate opinions in a unidirectional manner rather than to engage in dialogue' (Uldam and Askanius, 2013, p. 1191). If so, as Collins and Nerlich (2015) stated, 'then their views become more entrenched: there is little potential for them to develop their perspectives, for mediation or for novel discourses to emerge' (p. 192).

Despite the general feature of social media, i.e. the tendency of low reciprocity in the discussions, we do not know how climate strikes changed the reciprocity of climate change discussion networks. Generally, climate strikes are a more concrete and engaging topic than climate change, as they can be considered an issue that involves worldwide offline movements and concrete in/out behavioural choices. I propose that participants in the discussion network of climate change tend to interact with each other more often than before climate strikes became prominent. It is worth noting that the participants in two periods are not supposed to be the same group of people. In other words, some new participants joined in Period 2 and some participants form Period 1 stayed in the discussion in Period 2.

> Hypothesis 2a. Climate strikes increased the reciprocity of the climate change discussion network on Twitter.

4.2.2.2 Equality

In the informal zone of the public sphere, structural equality is achieved when participants have equal access to speaking opportunities and equal distribution of voice among the speakers (Hagemann, 2002). Because I am interested in the discussions on Twitter rather than access to Twitter as a platform, only this dimension, equality distribution of voice, will be measured in this chapter. Equality in the idealised state would suggest that all participants ought to contribute equally. Equality of interests could be measured by the extent to which contributions to discussions are evenly distributed among all participants, which can be operationally tested by centralisation in network analysis (Hagemann, 2002) (e.g. in-degree, out-degree and degree, which are defined below).

Because computer-mediated discussions provide an almost infinite canvas for new messages, the scarce resource becomes attracting attention, particularly replies to new threads. While retweets and favourites also demonstrate attention, this chapter focuses on replies as the form of discussion. Reply count is a useful indicator of the value of or interest in that topic (Himelboim, 2008). Although that may be bad attention, whether the attention is good or not is not discussed in this chapter. In online discussion forums, nodes are participants and links are replies they send to one another's posted messages. The emphasis on replies as links is important, because participants benefit from replies. Participants who receive replies to their posts have been found more likely to continue and participate in a discussion (Arguello et al., 2006). In the context of political discussions, receiving replies is especially beneficial to participants. By attracting a large number of replies to a message, a participant can shape, to some extent, the topics that are discussed. Replies constitute directed links, as posting a reply to one's posted message does not guarantee that one will reciprocate by posting a reply back. Participants, therefore, can differ in terms of the number of participants they post replies to (out-degree, which is an indicator of a user's level of activity) and the number of participants that post replies to their message (in-degree). Within the context of political discussions, a participant with a high in-degree is more likely to influence the topics that are being discussed and thus, in a sense, set the agenda (Himelboim, 2010). In the idealised situation, the equality of status among participants must apply so 'that no one speaker (or group of speakers) could rightly monopolize the powers and means of assertion, disputation, and persuasion' (Keane, 1984, p. 160). But, if only a few are successful in attracting attention to the information they present, can we still argue that they are equal (Himelboim, 2010)?

Though the majority of the scholarship in social media research has focused on 'receiver' effects (popularity), some scholars have also started to examine 'sender effects' (activity) of online expression, which has direct relationships with citizen participation (Rojas and Puig-i-Abril, 2009). In this chapter, I will analyse equality with reference to both popularity (in-degree) and activity (out-degree), as well as degree, which is the sum of in-degree and out-degree. However, instead of simply measuring equality using in-degree, out-degree and degree, in this chapter I introduce the Gini coefficient and the Lorenz curve, which help to analyse the centralisation and measure the equality.

The Gini coefficient, as a measure of inequality in distributions, has been mainly used in economics and sociology to describe inequality in the distribution of a given resource, such as wealth, among the individuals of a population, but also in physics to describe other quantities. For example, Crucitti et al. (2006) conducted a hierarchical clustering analysis based on the distributions of centrality using the Gini coefficient and Lorenz curve to study the centrality in urban street patterns of different cities. The Gini coefficient was an index first presented by Corrado Gini (1884–1965) in the book *Variability and Mutability* (*Variabilità e Mutabilità*) in

1912, and is defined as 'the mean difference from all observed quantities'. Adapted to degree distributions, the Gini coefficient is formally defined as the normalised expected difference in degree between two randomly selected nodes, given by Gini (1912), Dalton (1920) and Ceriani and Verme (2011). Gini also discussed the Gini coefficient and its relation with the Lorenz curve in a 1914 paper that was later translated to English (Gini, 2005; Ceriani and Verme, 2011). The Lorenz curve is a convenient graphical method of exhibiting distributions, which was developed by the American economist Max O. Lorenz in 1905 to represent income inequality (Lorenz, 1905). The Lorenz curve shows, 'for the cumulative percentage x% of the population (plotted on the x-axis) arranged from poorest to richest, their cumulative percentage y% of the total income (plotted on the y-axis)' (Hu and Wang, 2008, p. 3771).

For degree distribution, the Lorenz curve plots the cumulative proportion of the nodes ordered by degree against the cumulative proportion of the degree held by those nodes and also includes a (diagonal) reference curve that indicates the Lorenz curve for a distribution where all nodes have the same degree. A greater 'bend' away from the reference curve indicates greater inequality. The index of the Gini coefficient ranges between 0 and 1, with 0 representing maximum equality and 1 representing maximum inequality.

Hu and Wang (2008) defined the heterogeneity index of a network according to the Gini coefficient of the degree distribution of a network and the Lorenz curve, and the rule is that '[t]he heterogeneity index of a completely homogeneous network is 0; however, the heterogeneity index of a completely heterogeneous network will approach 1' (p. 3770). Badham (2013) compared the Gini coefficient with four other commonly used statistics for the shape of distributions – variance (Snijders, 1981), power-law exponent (Barabasi and Albert, 1999), centralisation (Freeman, 1978) and hierarchisation (Coleman, 1961). Unlike the limitations of other statistics – for example, 'the coefficient of variation is difficult to interpret in the context of a highly skewed distribution' (Badham, 2013; p. 224), and the power-law exponent is more suitable for 'strongly skewed, large, technologically supported information networks such as World Wide Web links or email address books' (Badham, 2013; p. 214) – the Gini coefficient was recommended by Badham (2013) as the most suitable shape measure for degree distributions, because it has desirable theoretical properties, and is appropriate for any shaped distribution. In their recent paper, Liang and Lee (2022) employed the Gini coefficient to measure the popularity inequality of the distribution of replies in a forum to analyse the organization through communication in a networked movement. In this chapter, I apply the Gini coefficient to measure the equality of the network's centralisation (degree distribution) and accompany it with the visual tool of the Lorenz curve.

I propose that there were more superstars in the discussion network like Greta Thunberg after climate strikes became a prominent topic on Twitter, which led to inequality. This observation leads me to another hypothesis.

> Hypothesis 2b. Climate strikes reduced the equality of the climate change discussion network on Twitter.

4.2.2.3 Diversity

The diversity dimension of deliberation emphasises the inclusion of multiple voices, concerns, values, perspectives and claims. Schneider (1997) measured diversity by the number of days that the size of newsgroup changes and the presence of multiple conversational patterns within threads of messages. Taking a structural perspective, rather than getting contents of tweets involved, in this chapter I operationalise diversity in a discussion network as the mean of the number of unique users in the network per day. A higher mean of unique users per day means higher diversity, as more unique users in a day means there is more potential to have different ideas.

> Hypothesis 2c. Climate strikes increased the diversity of climate change discussion networks on Twitter.

Table 4-1. Summary of hypotheses and operational variables

Hypotheses	Operational variables
1. Climate strikes raised the visibility on Twitter of the issue of climate change.	Reply counts per day; cumulative number of participants in the discussion
2. Climate strikes increased the deliberative potential of climate change discussion networks on Twitter.	
2a. Climate strikes increased the reciprocity of the discussion network of climate change on Twitter.	Reciprocity
2b. Climate strikes reduced the equality of climate change discussion networks on Twitter.	Equality
2c. Climate strikes increased the diversity of climate change discussion networks on Twitter.	Diversity

So far, I have operationalised the measurements of deliberative potential (reciprocity, equality and diversity), as summarised in Table 4-1. The following section will bring the data into account.

4.3 Methods

4.3.1 Data

Unlike the Twitter profile feed, which is controlled by a particular actor, the community-generated hashtag convention allows anyone to use a hashtag for any tweeted message. A difference between Twitter and social networking sites such as Facebook is that the relationship between following and being followed is not necessarily a two-way street on Twitter. Hashtagged messages might raise the possibility to disperse widely in unpremeditated combinations across a variety of feeds and networks (Ausserhofer and Maireder, 2013). The hashtag suggests the contours of a network cutting across the issue being discussed, where diverse users, different temporal and spatial regions are connected (Ausserhofer and Maireder, 2013). Therefore, I collected the climate change-related tweets and relationships using the hashtag #climatechange.

I collected tweets with the hashtag '#climatechange' every four days, and the dataset covers the period 10 September 2018 to 10 September 2019. To capture the discussion of people who were interested in climate strikes, I ranked the frequencies of hashtags in the dataset, and found the hashtags related to climate strikes in the top 50 hashtags (Table 4-2). This shows that #climatestrike was the most popular. Therefore, I focus on #climatestrike in this chapter to explore how the discussion of climate strikes impacted the discussion of climate change. To get rid of the impact of language differences on the structure, I extracted the contents in English only. There were 72,603 replies and 55,711 participants involved in the discussion network of climate change. In other words, 55,711 users posted replies with the hashtag #climatechange. There are 1,901 replies and 1,861 participants in the intersection part of the discussion network of climate strikes and climate change. In other words, 1,861 users used both #climatestrikes and #climatechange in the same reply.

Table 4-2. Hashtags related to climate strikes in the discussion network of #climatechange

Rank	Hashtag	Frequency
9	#climatestrike	1901
19	#fridaysforfuture	964
46	#gretathunberg	416

4.3.2 Analysis

To test Hypothesis 1, I calculated the daily counts of reply tweets that contained #climatechange (RHS axis) and daily counts of reply tweets that contained both

#climatechange and #climatestrike at the same time (LHS axis), i.e. the intersection part of the discussion networks of #climatestrike and #climatechange, as shown in Figure 4-1. To show the difference, the scale for counts of #climatechange is 14.29 times the intersection of #climatestrike and #climatechange (hereafter marked as #climatestrike∩#climatechange). As we can see, before there were many discussions of climate strikes, discussions of climate change were not very popular. There was a small peak in January in discussions of climate change right after discussions of climate strikes in climate change emerged (users used #climatestrike and #climatechange at the same time). Then, after discussions of climate strikes in climate change peaked in February and declined in April and May, the discussion of climate change became dramatically more active from June. However, we cannot tell whether the rise of reply counts in the network of #climatechange was directly caused by the discussion of climate strikes. More analysis is needed to make a conclusion for Hypothesis 1.

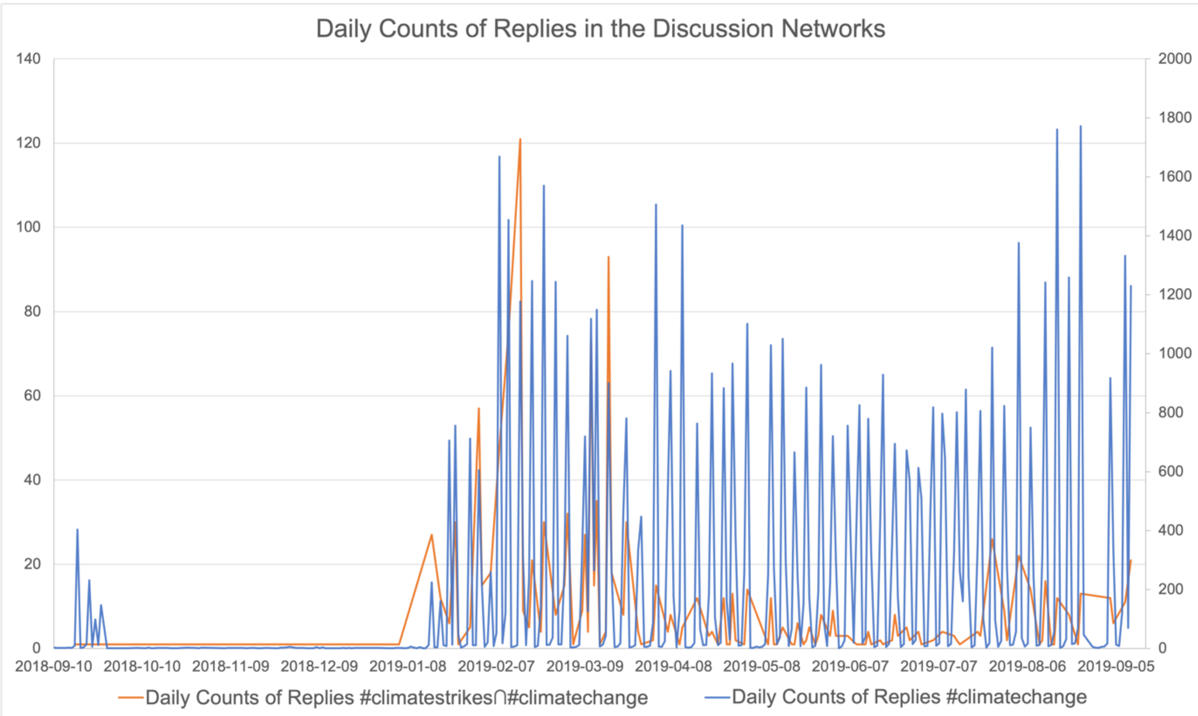

Figure 4-2. Daily counts of replies in the discussion networks

Figure 4-3 below shows the cumulative number of participants in the two discussion networks. The inflection point marks the peak increasing rate of the cumulative curve of #climatestrike∩#climatechange, which means that, on 21 February 2019, the number of new participants increased most quickly in this discussion network.

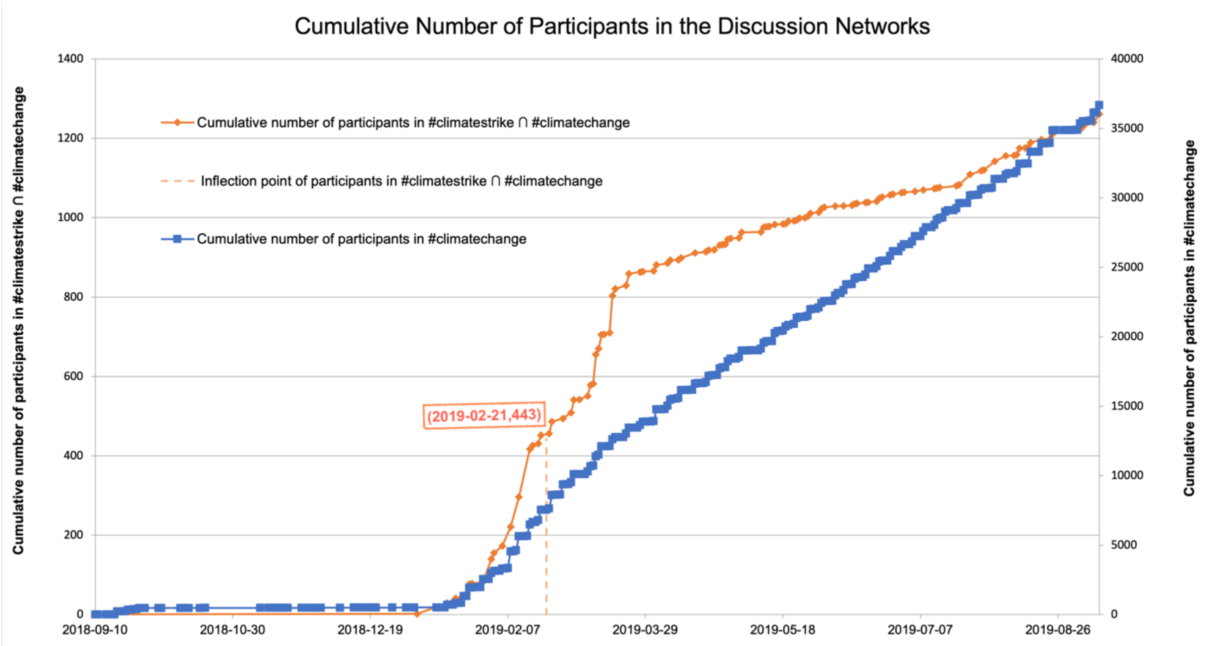

Figure 4-3. Cumulative number of participants in the discussion networks

As shown in Figure 4-3, the inflection point of users participating in the discussion of climate strikes in climate change was on 21 February 2019, in other words, the increasing rate of new participants involved in the discussion arrived at the peak value then, and the discussion of climate strikes became prominent. Therefore, to test Hypothesis 2, I divided the year into two periods – before and after 21 February 2019 – and compared the two discussion networks of #climatechange. More specifically, a pair of networks was constructed to show the difference of deliberative potential between Period 1 and Period 2 of the discussion networks of #climatechange from equality, reciprocity and diversity. The network graphs of the giant components in Period 1 and Period 2 are shown in Figure 4-4 and Figure 4-5, respectively. The giant component is the largest connected component in which each node is connected with each other. Showing the giant components can get rid of the noise of the unconnected parts and isolated nodes, so that the visualisation is less complicated. The graphs were generated using Gephi, with the ForceAtlas2 layout. The statistics are shown in Table 4-3.

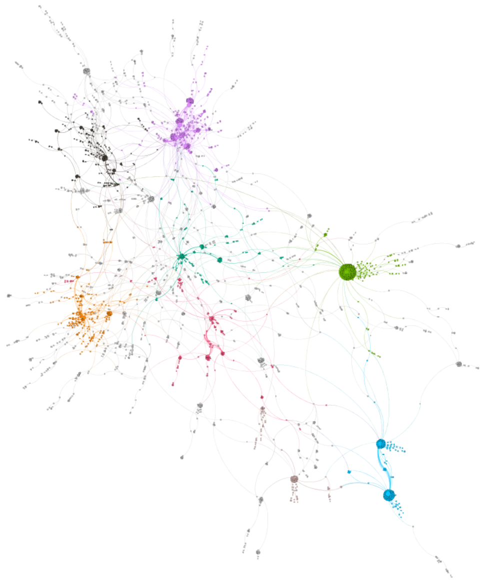

Figure 4-4. Network graph of #climatechange discussion network in Period 1

Note: The colour denotes the modularity class, which shows the belonging of the node in the module or cluster. The node size denotes degree.

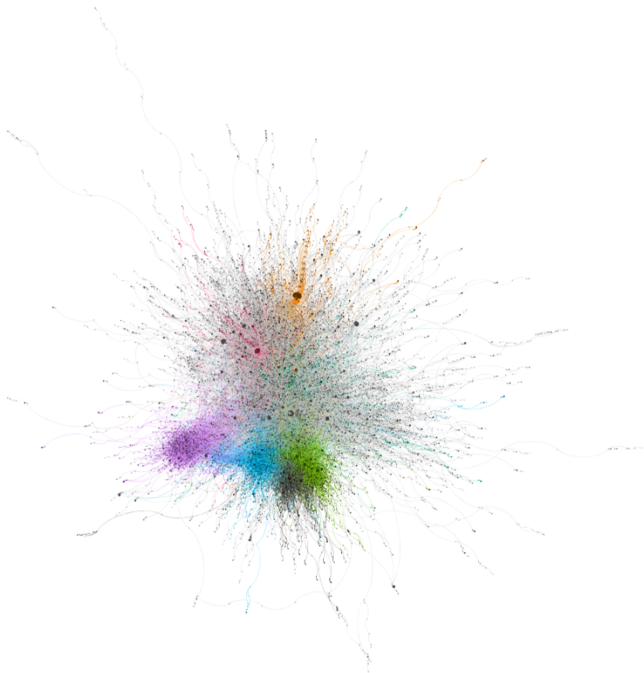

Figure 4-5. Network graph of #climatechange discussion network in Period 2

Note: The colour denotes the modularity class, which shows the belonging of the node in the module or cluster. The node size denotes degree.

Table 4-3. Changes of deliberative potential in the discussion networks of #climatechange

Indicators	Period 1 (10/09/2018–21/02/2019)	Period 2 (22/02/2019–10/09/2019)	Changes in deliberative potential
Density	0.00011	0.00003	Density ⇩
Reciprocity	0.00499	0.00665	Reciprocity ⇧
Gini (degree)	0.43928	0.54936	Equality ⇩
Gini (in-degree)	0.84911	0.85196	Equality ⇩
Gini (out-degree)	0.51338	0.63344	Equality ⇩
Unique users	11,426	47,109	Diversity ⇧
Unique users/day	69	235	

The density describes the portion of the potential connections in a network that are actual connections. It decreased in Period 2, which shows that, compared to Period 1, users were less likely to reply to each other, and this is mainly because there are significantly more participants in the network (more than four times the previous number of users). However, given the much smaller density seen in Period 2, the reciprocity increased, which means that participants tended to reply to others' replies. In other words, people were more willing to have a further discussion with others to exchange ideas in Period 2, even when it was relatively more difficult with more users, which confirms Hypothesis 2a. Higher reciprocity in Period 2 brought higher deliberative potential.

Regarding equality, as 0 represents maximum equality and 1 represents maximum inequality, the Gini coefficients in Table 4-3 show that networks in both periods are unequal, especially on in-degree, which indicates that there were superstars who were very popular in the network, e.g. Donald Trump was the one who received most replies in both periods. When we compare the equality of the two periods, the differences are relatively small. Furthermore, the discussion network became more unequal in Period 2, especially on out-degree, which shows that there were some participants who were much more active than others. The most active one, which sent the most replies to others, changed from the official account of Bank of America News to a media commentator who was interested in climate politics. Inequalities in both periods indicate that the discussion of climate strikes did not change the reality that the discussion of climate change on Twitter is unequal, and even exacerbated it, which can verify Hypothesis

2b. Lorenz curves help to visualise the differences; these are shown in Figure 4-6 below

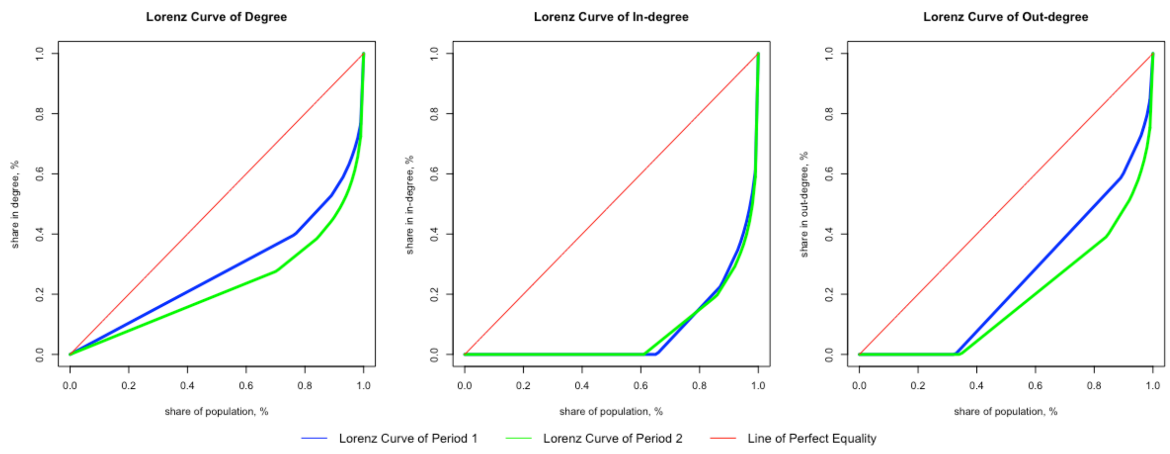

Figure 4-6. Lorenz curves of degree, in-degree, and out-degree in two periods

If the Lorenz curve (the blue and green lines in Figure 4-6) moves closer to the line of perfect equality (the red line in Figure 4-6), it means a reduction in inequality. But, as we can see, the Lorenz curves in Period 2 are all further from the line of perfect equality than in Period 1, especially the degree distribution and the out-degree distribution.

As for diversity, the average number of unique users in the discussion network per day in Period 2 was more than three times (3.4) that of Period 1, which reveals that there were many more different users engaged in the discussion of climate change; in other words, diversity increased in Period 2. To some extent, it shows that the climate strikes attracted more diverse users to participate in the discussion of climate change on Twitter, which increased the deliberative potential.

To sum up, the above results verified the hypotheses. Discussion of climate strikes raised the visibility on Twitter of the issue of climate change, and increased the deliberative potential of the discussion network of climate change given increased reciprocity and diversity. However, the discussion of climate strikes could not reduce the inequality in the discussion network. In contrast, it increased inequality, which is harmful to the deliberative potential.

4.4 Discussion and conclusion

This chapter reviewed the measurements that other researchers used to examine deliberation, chief among which is the framework of four dimensions (reciprocity, equality, diversity and quality) of the ideal public sphere proposed by Schneider (1997). I chose to operationalise the measurements in a structural manner to propose a viable approach to examine the interactions among users on social media with big data. In this case study, I explored whether and how climate strikes impacted the deliberative potential of the discussion of climate change. I chose this approach because, before measuring exactly the extent to which the discussion was deliberative, it is crucial to understand the nature of online deliberation and find changes of the deliberative potential of discussions while the discussions evolve. I took the social movement climate strikes as a key event to find the changes in discussions of climate change. Given the literature, I had two core hypotheses: Hypothesis 1. Climate strikes raised the visibility on Twitter of the issue of climate change; Hypothesis 2. Climate strikes increased the deliberative potential of climate change discussion networks on Twitter.

The results indicate that, after the discussion of climate strikes became prominent, the discussion of climate change became more reciprocal and diverse, while also less equal. At the beginning of this chapter, I posed the question of what measurable changes users discussing climate strikes brought to deliberation in climate change discussions on Twitter. From the increased reciprocity shown in the results, I found that, after climate strikes, participants tended to have further discussions with their discussion partners on the topic of climate change. They were more willing to engage in dialogue rather than only demonstrating opinions in a unidirectional manner, which increases the potential for participants to develop their views. This finding aligns with the conclusion of Collins and Nerlich's research that user comments on articles about climate change in *The Guardian* showed potential for engaging in dialogue and for more interaction (Collins and Nerlich, 2015). The increased diversity reveals that there were more unique users joining the discussion of climate change after climate strikes. In other words, rather than engaging the same group of people, in the second period, there were many more different participants who joined the discussion of climate change, which fortifies the potential of inclusion of multiple voices. Even though they may have similar ideas, as scholars raised concerns about 'echo chambers', the potential of the existence of different ideas increased after climate strikes became prominent.

The co-occurrence of higher reciprocity and diversity provide a better public sphere that participants have deeper discussions with multiple voices. To some extent, the discussion of climate change became more deliberative, which is good news for people who are trying to raise public awareness of climate change. Through more deliberative discussions, it is more likely that the plurality of environmental values can be effectively assessed and considered in the decision-making process (Warren, 1996).

As mentioned in Section 4.2.2.2, equality would suggest that all participants should contribute equally to the idealised communication situation. However, the ‘rich get richer’ effect, also known as ‘preferential attachment’, occurs on most social media platforms (Kunegis et al., 2013), which means it is hard to achieve perfect equality on Twitter. Therefore, it is less surprising that both discussions of climate change in the two periods are unequal. However, discussion in the second period became more unequal, which indicates that there were more superstars in the discussion network of climate change after climate strikes had been highly discussed. When superstars attracted more attention, others’ ideas became relatively hard to be heard. In this way, other users lost the equal opportunities to contribute to and influence the discussion, so that agenda could be set by these superstars. What’s more, with the existence of superstars, many users passively became silent in the discussion. In turn, the motivation of these users for actively participating in the discussion would be eliminated, which can be harmful to deliberation.

Although participants in Period 2 had a deeper discussion, shown in the increased reciprocity, and there were more diverse participants, the discussion network of climate change was still unequal, and even more unequal. This result shows that a large number of newly joined participants brought more attention to superstars, rather than shared attention from superstars. This shows that, as the discussion of climate change on Twitter evolves, it becomes more centralised on several opinion leaders. Although it is harmful for deliberation, to take it positively, for people who are advocating collective actions for climate mitigation, such as policymakers and NGOs, it is much easier to achieve more efficient communication outcomes via collaborating with these opinion leaders.

This chapter tests the deliberative potential of online climate change discussions on Twitter through the changes brought by discussions of climate strikes. This case study provides empirical evidence for the debate between cyber-optimists and cyber-pessimists. Although there is no simple answer to whether we should be optimistic or pessimistic towards the Internet or social media, we have already found that climate strikes did change the deliberative potential of the discussion of climate change. The discussion of climate strikes increased the potential by enhancing reciprocity and diversity, while decreasing the potential by aggravating equality.

This chapter is not free of limitations. First, I only analysed replies in English, which resulted in the difficulty of generalisation the findings to climate change discussion in other languages. Second, the dataset in this chapter was collected using the single hashtag #climatechange, but some users also use other hashtags, such as #globalwarming, to participate in the discussion of climate change on Twitter, and this may have different features as well. For example, Shi et al. (2020) stated that, although the discourse around #climatechange and #globalwarming shared many similarities, #climatechange demonstrated a more scientific perspective than #globalwarming, which is more politicised, based on the data covering 2009 to 2018.

This chapter is a structural study. It is crucial to look at the structure of discussion networks based on users' interactions, and it is feasible for other researchers to adapt my measurements for related empirical research. However, it is also important to measure the deliberative potential of the discussions based on the arguments embedded in the tweets. Future studies should work more on the content, such as the diversity and quality of tweets and replies posted by participants. Also, it is important to consider the diversity of participant types, e.g. the ratio of policymakers, scholars, the general public etc. Future studies could also look at a variety of different moments when new movements emerged and then assess whether they increase or decrease deliberation based on my research.

From this chapter we have seen the positive evidence of the deliberative potential of discussions on Twitter about climate change from the perspective of discussion networks. In the next two case studies, I focus on user-generated content. This gives a better understanding of how users collectively make sense of climate change and related emerging technologies.

Chapter 5 Understanding Collective Framing of Climate Change via Hashtag Co-occurrence Networks on Twitter

5.1 Introduction

After the previous chapter's examination of the deliberation in climate change communication on Twitter from the perspective of discussion network structure, I now turn to the examination of a strategic action in deliberation, in particular how people collectively make sense of climate change. As defined in Chapter 2, online deliberation in this thesis is the informal online discursive process in which participants express their opinions and discuss with each other, with the potential goal of achieving mutual and collective understanding about political issues. Sense-making here means people define an issue through framing in communication (Chong and Druckman, 2007).

We can begin the current examination with the recognition that the majority of climate change communication research has focused on mass media, such as coverage of climate change in newspapers or television, even if, on social media, scholars have tended to emphasise elites, celebrities or politicians and still tend to regard the general public as passive receivers of information, which is true in the mass media but not on social media. However, the content that users who attempt to change the way people think about issues generate on Twitter can be regarded as the outcome of framing, which is a strategic action in deliberation (Reese et al., 2001). People express their ideas on social media, and we can understand these ideas through connected concepts that users posted in the corpus. On Twitter, people come together to express their opinions about climate change by selecting and connecting specific texts (including hashtags), emojis, images and videos. The content collectively generated by all users on Twitter form a discussion network, from which we can see what climate change as a topic looks like, and how it can influence others' views, which will jointly shape the collective sense-making of climate change, and might further influence policymaking. This deliberative process is defined in this chapter as 'collective framing'.

Instead of studying any other content, such as the whole tweets, images or videos, this chapter takes the hashtag as the subject of analysis. In particular, I seek here to track deliberation as an ongoing process by analysing hashtag co-occurrence networks. A hashtag is a critical element in tweeting. As the operator # in hashtags explicitly reflects users' emphasis, a hashtag can be regarded as an indicator of framing (Meraz and Papacharissi, 2013). In the hashtag co-occurrence networks, hashtags are treated as nodes, and the co-occurrences of hashtags to each other are treated as edges. In this way, we can apply network analysis to explore and examine the roles of different hashtags in the network and the underlying factors that drive the formation of the networks. I argue that, over time, the overall connections between hashtags – as indicated by hashtags being used together – that are produced by all users who had ever entered the conversation, can indicate the process of the collective framing. That is, in using hashtags in particular networked ways, users associate different concepts, and work to collectively frame the topic. Rather than digging out the causal relationship between users' psychological process and their behaviours, or between the content and its impact on their behaviours or on reality, this chapter seeks to describe how Twitter users frame climate change via selecting and connecting different hashtags, and to interpret the structure of the hashtag co-occurrence networks, which can be seen as the direct outcome of the connecting behaviours. The collective framing in this chapter is a deliberative way for Twitter users to join the discussion by selecting and connecting different hashtags together and generating overall frames over time. I focus on two framing processes to examine users' framing using hashtags on Twitter: frame amplification and frame articulation, as defined in Section 5.2.1 below. This chapter intends to explore what hashtags users selected in their tweets and how users connect different hashtags. Instead of specific hashtags, I manually code the hashtags into different categories, and analyse what kinds of hashtags users selected.

This chapter seeks to answer the following research question: RQ2. How did users collectively frame climate change via hashtags? Specifically, there are three subquestions: RQ2a. What kinds of hashtags were selected to talk about the topic of climate change on Twitter? RQ2b. What hashtags played important roles in the framing process? RQ2c. How did users associate hashtags related to climate change on Twitter? RQ2a examines the framing process from the perspective of framing amplification, and RQ2b and RQ2c are from the perspective of framing articulation, which will be explained in detail in the following sections. This chapter also takes time into account to examine whether users' framing changed over time.

In addition to the climate strikes, mentioned in Chapter 4, the year 2018 is also endued with special meaning in the history of climate change owing to the release of the IPCC Special Report Global Warming of 1.5°C (SR15) in October 2018 and the 24th United Nations Framework Convention on Climate Change's (UNFCCC) Conference of Parties (COP), held from 2 December to 14 December 2018. COP is an annual meeting at the UN and acts as a venue to discuss the progress and establish obligations with regard to climate change (UN Climate Change, 2019). 'By 2015 climate scientists were reporting that restricting emissions consistent with human-induced warming of 1.5°C was probably advisable' (Gills and Morgan, 2020, p. 893), which became a part of the Paris Agreement, an outcome of COP21 in Paris in 2015. During COP21, UNFCCC formally requested the IPCC to undertake a Special Report on 1.5°C during COP21. The 24th COP (hereafter COP24), taking place in the wake of the release of the SR15, was then seen as the most important climate negotiation since 2015. COP24 was seen as a critical juncture for countries to reach agreements on the rules for reducing emission to achieve 1.5°C and to set stronger climate action. Compared to the Climate Strikes, which were a series of informal mass mobilizations, COP24 is an event which happened during a short period of time, which results in condensed discussions on social media. Also, online discussions about COP24 would be more specifically policy related. Therefore, compared to climate strikes, COP24 offers a more focused time period in which to analyse collective framing. This chapter examines how the collective framing of climate change on Twitter changed in the aftermath of the COP24 conference.

To construct the hashtag co-occurrence network, I processed the Twitter data that was used in Chapter 4 to obtain the hashtags and their co-occurring relationships. To find out the categories of hashtags that were selected by users, I applied manual coding to group the hashtags into different categories. By doing this, I can answer RQ2a and prepare for exploring RQ2b and RQ2c. As I compare the changes before and after COP24, a timepoint to divide the whole period is needed. I use the inflection point, which was also explained and applied in Chapter 4, to find the day that COP24 became prominent on Twitter, that is, the day when the increasing rate of the frequency of #cop24 arrived at its peak. Then, to answer RQ2b, I identify important hashtags (i.e. hubs and bridges) in the networks based on the hashtags' degrees and betweenness centralities before and after COP24 became prominent. To answer RQ2c, I will compare the network statistics (degree assortativity and categorical assortativity) of the full networks before and after COP24 became prominent to find the difference at the network level. At the same time, I refine the networks by the minimum spanning tree (MST) method to find out how hashtags are substantially connected with each other and show the network structure more clearly, and to apply exponential random graph models (ERGMs) on the MST-filtered network to answer RQ2c. Specifically, I use ERGMs to test the hypothesis: hashtags of the same category tend to be associated together. It examines whether users tend to associate the hashtags of the same category together in the same tweet (the assortativity of the co-occurring hashtags).

5.2 Background

5.2.1 Collective framing and hashtags

As mentioned in Chapter 2, Entman (1993) defined framing as ‘select[ing] some aspects of a perceived reality and mak[ing] them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described’ (p. 52). As stated by Baumgartner and Mahoney (2008), two facets of framing exist in lobbying: ‘individual-level framing’ and ‘collective issue-definition’, which are different but related to each other. The differences are ‘whether different advocates attempt to frame the issue they are working on to be about one dimension rather than another and whether they tailor their arguments to the target – spinning the issue in different ways to gain political support’ (Baumgartner and Mahoney, 2008, p. 444). Similar to lobbying, users on social media also have different political stances and tailor their arguments, which might strictly be called opinions rather than arguments, to spin the political issues accordingly to gain others’ support. But individual users are different from lobbyists as the individual users are not necessarily strategic in their efforts. Rather than focusing on the formal lobbying and parliamentary process, this chapter sheds light on the informal discursive process and focus on the collective issue-definition in the topic of climate change on Twitter.

A range of studies have investigated the framing of political issues on social media. However, the majority have only examined the framing actions of celebrities or politicians. For example, Hemphill et al. (2013) collected Twitter data to analyse how members of the US Congress use hashtags to frame issues, and Brooks et al. (2021) surveyed 40 global advertising industry practitioners and influencers to study how they gain celebrity capital on social media. Some scholars have recognised the important role of the public; for example, Baumgartner and Mahoney (2008) stated that ‘[p]olicy decisions are greatly affected by the way issues are understood collectively by policy-makers and the public’ (p. 435). However, how the public participates in framing issues, rather than only being the receiver of the framings of strategic actors, has not been widely studied yet. Given the public’s increasing role in communication on social media, this chapter focuses on the collective issue-definition facet of framing in which Twitter users engage in public climate discourse.

Although this chapter focuses on all the users who are engaged in the topic on Twitter, rather than focusing on social movements or movement members, it is still worth investigating what the literature about framing in social movements found about the discursive processes. This is not only because of the limited literature on the framing of all the actors but also because social movements involve various actors, and we can get some hints about the wider set of users on Twitter. A group of scholars have focused on the frames used by social movement organisations or environmental movement organisations, so-called ‘collective action frames’. In the movement framing literature, the ‘collective action frame’ is defined by Benford and Snow (2000) as ‘action-oriented sets of beliefs and meanings that inspire and legitimate the activities and campaigns of a social movement organisation’ (p. 614), of which the key framing tasks are: ‘diagnostic framing’ (problem identification and attributions), ‘prognostic framing’ (articulation of proposed solutions or alternative arrangements) and ‘motivational framing’ (action mobilisation) (Snow and Benford, 1988). As stated by Benford and Snow (2000), discursive processes of framing refer to ‘the talk and conversations—the speech acts—and written communications of movement members that occur primarily in the context of, or in relation to, movement activities’ (p. 623), and collective action frames are developed and generated by ‘two basic interactive, discursive processes: frame articulation and frame amplification’ (p. 623). Frame articulation involves ‘connection and alignment of events and experiences so that they hang together relatively in a unified and compelling fashion. Slices of observed, experienced, and/or recorded ‘reality’ are assembled, collated, and packaged’ (p. 623), and frame amplification involves ‘accenting and highlighting some issues, events, or beliefs as being more salient than others’ (p. 623). The accented elements in frame amplification can provide a conceptual peg for connecting multiple events and issues in the articulation process, and signify the larger frame of which it is a part (Benford and Snow, 2000). I assume that the hashtag co-occurrence networks in this chapter involve both processes, as users select certain hashtags (frame amplification) and connect them in different ways (frame articulation), which will be explained in more detail below.

As introduced in Chapter 2, hashtags can be taken as a ‘performative statement’ by users and can gather users around common interests or issues without following relationships with others, which can therefore create emergent publics. Hashtags have also been regarded as topic markers (Rambukkana, 2015), or a tag of a user’s community membership (Yang et al., 2012). There are also scholars who treat hashtags as frame markers and a means for the collective issue-definition process, such as Papacharissi and de Fatima Oliveira (2012), Meraz and Papacharissi (2013) and Ince et al. (2017). A hashtag is also regarded as a typical indexing behaviour. As argued by Ince et al. (2017), ‘indexing is important because it represents a collective attempt to create categories in an otherwise unruly collection of texts’, and the use of indexing or labelling functions is a way that the public interacts with frames on Twitter. The use of hashtags, as one kind of indexing behaviour, is a form of decentralised interaction (or ‘distributed framing’, as Ince et al. (2017) called it), which can free analysis of the framing process from the celebrities or other highly visible users and give the wider public ability to participate in the process. The so-called ‘distributed framing’, on the other hand, expresses a meaning similar to the ‘collective framing’ used in this thesis, in that the users frame the topic altogether.

As suggested by Meraz and Papacharissi (2013), ‘[f]or emerging issues with no consensus on a single hashtag, this inherent competition among hashtags for stickiness or traction symbolically comes to represent the ebb and flow of an issue’s interpretation longitudinally, be it content based or sentiment based’ (p. 144). When it comes to climate change, as it is a controversial topic, there are various hashtags engaged in the competition, such as subtopics or related topics. In the longitudinal process, a selected group of hashtags will be popular after the hashtag competition, which can be considered the dynamic competition of frames. ‘These hashtags that gain widespread adoption thus enact, enable, and sustain the framing of select interpretations, aspects, or frames, to an event over time’ (Meraz and Papacharissi, 2013, p. 144). Following this camp, in this chapter I regard hashtags as indicators of framing.

Compared to the ‘primary actors’, i.e. Twitter accounts for organisations and individuals, hashtags are regarded as ‘secondary actors’ by O’Neil and Ackland (2018), because they need agency to make connections with other actors. ‘Primary actors also promote issues via the use of hashtags and, in doing so, create ties between these issues in semantic space (two hashtags are connected in semantic space if a Twitter user features both hashtags in a tweet)’ (O’Neil and Ackland, 2018, p. 15) Scholars have started to analyse hashtag co-occurrence networks to identify the relative prominence of individual hashtags and the strategies taken by users to frame the political issue (Wang et al., 2016).

5.2.2 Hashtag co-occurrence network

Different types of hashtags exist – for example, politics (#maga: ‘Make America Great Again’), geographical locations (#Europe), conferences (#COP25), and social movements (#climatestrikes) – and users can use different types of hashtags in a single tweet for their own purposes, for example to connect the topic with other topics. Nonetheless, the majority of the studies related to hashtags have looked at the role of a single hashtag, such as Meraz and Papacharissi’s (2013) focus on #egypt, which was used with high frequency during the 2011 Egyptian uprisings. Less is known regarding how hashtags of different nature or thematic types may frame the upper-level topic differently and how users connect different hashtags together to frame the political issues. What’s more, the kinds of hashtags that have been used in the topic of climate change on Twitter have not been studied yet. In this chapter I seek to explore the **frame amplification** process by answering RQ2a:

> RQ2a. What kinds of hashtags have been selected on the topic of climate change on Twitter?

The hashtag co-occurrence network is constructed by hashtags that appear in the same tweet. For example, if #A, #B, and #C are in the same tweet, there are three kinds of dyadic connections: #A–#B, #B–#C, and #A–#C. Individual users select different hashtags in their tweets. When it comes to the massive number of users on Twitter, the hashtag co-occurrence network can reveal the structure and salient information about how users frame the topic as a whole, which has been defined in Section 5.2.1 as 'collective framing'. For instance, Ince et al. (2017) studied how the emergent social movement Black Lives Matter (BLM) presented on Twitter, and examined how users interact with this topic using hashtags to modify the framing of the social movement. Specifically, they analysed the co-occurrence of the hashtags that are also used in tweets when users refer to BLM in order to 'add and extend to the movement's original meaning' (p. 1815). Following Ince et al. (2017), rather than focusing on individual hashtags, as Papacharissi and de Fatima Oliveira (2012) did, I study the hashtag co-occurrence networks, using network analysis. This way to analyse text is similar to semantic network analysis. Semantic network analysis is defined as 'network analysis using written texts to identify salient words and concepts in order to extract underlying meanings and frames from the structure of concept networks' (Shim et al., 2015, p. 58). Yang and González-Bailón (2018) suggested that 'semantic network analysis is particularly suitable to represent and explain public opinion as conceptualised by discursive and deliberative theories of democracy' (p. 328). Semantic network analysis can 'highlight the most salient information in a body of text by assessing the networks that emerge' (Featherstone et al., 2020, p. 2), which is suitable for us to identify the frame amplification process. Complementary to the frequency-based techniques in content analysis, semantic network analysis emphasises the corpus's structural patterns by showing how concepts connect to each other (Diesner and Carley, 2005; Yang and González-Bailón, 2018), which can help to examine the frame articulation process. But my approach in this chapter is slightly different. I include all the raw hashtags in the network rather than identifying and interpreting the concepts embedded in the hashtags. Therefore, in this chapter I call this network analysis instead of semantic network analysis. Analysing hashtag co-occurrence networks can identify the outcome of the framing process, to which Twitter users who used two or more hashtags in their tweets have contributed collectively, which is an appropriate method to answer the research question of this chapter.

Some scholars have applied network analysis to analyse hashtags. For example, Haunschild et al. (2019) compared author keywords in publication with hashtags on Twitter as indicators of topics using semantic network analysis based on a publication set of climate change research. Their results indicate that publications with more common words are more likely to be tweeted than publications with scientific jargon, and Twitter networks can be used to visualise public discussions. Eddington (2018) investigated communication networks of text through Twitter hashtags and the linkage between Trump and extremist and white supremacist groups by analysing the hashtag co-occurrence network.

However, as summarised by Yang and González-Bailón (2018), most scholars using semantic network analysis have focused on elite political discourse (for example, Baden (2010); Leifeld (2013)), rather than the wider public's political discourse. As the focus of this thesis is online deliberation, it is crucial to study the discourse of wider publics. In this chapter, I do not differentiate between users' groups or roles; rather, I take them as a whole and analyse the hashtags they generated. This is related to the **frame articulation** process.

RQ2b. What hashtags played important roles in the framing process?

RQ2c. How did users associate hashtags related to climate change on Twitter?

To answer RQ2b, I identify the hashtags playing important roles in the networks and compare the two periods. To answer RQ2c, I made the following two hypotheses based on previous studies on network analysis (i.e. 'preferential attachment' and 'semantic homophily'). As summarised by Easley and Kleinberg (2010), the 'rich get richer phenomenon' or 'preferential attachment process' means that the popularity of the most popular items tends to increase faster than the popularity of the less popular ones. Cunha et al. (2011) explored the existence of preferential attachment in hashtags after analysing 1.7 billion tweets posted between July 2006 and August 2009. Based on this, I propose that less popular hashtags tend to be connected with more popular hashtags (H1). Šćepanović et al. (2017) called assortative mixing on semantic aspects of communication 'semantic homophily' to measure the assortativity of semantic attributes of the communication network on Twitter. It is worth noting that, instead of 'homophily', it is more proper in this chapter to call it 'assortativity', because hashtags are 'secondary actors' that require agency, as mentioned in Section 5.2.1. I propose that, in the hashtags co-occurrence network related to climate change, hashtags of the same category tend to be associated together.

H1. Less popular hashtags tend to be connected with more popular hashtags.

H2. Hashtags of the same category tend to be associated together.

H1 will be tested with the degree assortativity of the full network. To test H2, ERGMs are required. But it is challenging for ERGMs to test large and dense networks, especially regarding the computational time they cost. Instead of testing the full network, I apply MST to filter the network, which can reveal the network backbone.

Scholars have also suggested taking time into account when studying hashtags. For example, as argued by Faltesek (2015), 'studies of the circulation of hashtags need to pay particular attention to the temporality of their circulation' (p. 84), as the role of any particular hashtag may change over time (Bruns and Burgess, 2015), and 'meaning-production through and around hashtags occurs dynamically' (Eriksson Krutrök and Lindgren, 2018, p. 3). To take time into account, in this chapter I will take COP24 as a cut-off point to analyse the changes in the networks.

To summarise, I will answer the research question RQ2. How did users collectively frame climate change via hashtags? The research question will be answered through the following subquestions and hypotheses.

RQ2a. What kinds of hashtags were selected to talk about the topic of climate change on Twitter?

RQ2b. What hashtags played important roles in the framing process?

RQ2c. How did users associate hashtags related to climate change on Twitter?

H1. Less popular hashtags tend to be connected with more popular hashtags.

H2. Users tend to associate hashtags of the same category together.

5.3 Method

This chapter uses the same raw dataset as Chapter 4, which was collected from Twitter using NodeXL software (Smith et al., 2010) with the search term '#climatechange'. The dataset covers the period 10 September 2018 to 10 September 2019. Because in this chapter I analyse the user-generated content rather than the conversational relationships among users, I extracted the original tweets, i.e. tweets that do not specifically address any other user, which means that no retweets, mentions or replies exist in the dataset of this chapter. Then, with the help of the R package **stringr**, I extracted all the hashtags, i.e. text strings starting with '#', and removed all the non-ASCII characters and blanks. Then I converted all the hashtags to lowercase letters, because otherwise hashtags like '#climatestrike' and '#ClimateStrike' would be regarded as two different nodes in the hashtag co-occurrence network. I define two hashtags as connected if they appear within the same tweet. For example, in the tweet 'My daily news compilation on #climatechange #foodsecurity #globaldev, featuring this story and more... https://t.co/dMnfa5HxBW', the hashtags #foodsecurity and #globaldev are documented as co-occurring, and there is an edge between these two nodes in the network. Since all such hashtags would be connected to #climatechange and keeping #climatechange weakens other features of the network, I excluded it from the networks. In total, the dataset contains 97,950 hashtags.

To keep consistency, it was necessary to merge obvious synonyms, typos, and words with the same lexemes and keep only one of them. However, rather than stem similar words to their root words, which is a common approach in text analysis, I manually merged all the others to the most frequent one, as it is important to reflect users' preferences. For example, I merged 'amazonfire' and 'amazonfires' to 'amazonfires' (because there were more 'amazonfires' in the dataset; in other words, more users preferred to use 'amazonfires'); 'ausvotes19' and 'ausvotes2019' to 'ausvotes2019'; 'climat' and 'climate' to 'climate'. It is not a good approach to take hashtags equally in the coding process. As Entman (1993) warned, it is easy for content analysis to yield data that misrepresents the media messages that most audiences are picking up if coders treat terms as equally salient. For example, when one term appeared 100 times and the other term only appeared ten times in the corpus, treating the two items as equally important would not reflect the frequency that the terms had been used. This concern also applies in this chapter and should therefore be taken as a limitation. Nevertheless, to minimise this bias, after merging I only kept the top 1,000 hashtags that had the highest frequencies in the dataset for further analysis. More hashtags can be removed according to further analysis.

To compare the changes between the networks before and after COP24, we need to find a date when #cop24 became a relatively prominent hashtag. Applying a similar method to find the date in Chapter 4, I calculated the cumulative numbers of the hashtag #cop24, and found the inflection point on 1 December 2018 (Figure 5-1), which marks the date when COP24 became a prominent topic on Twitter and this is used to divide the whole year into two periods.

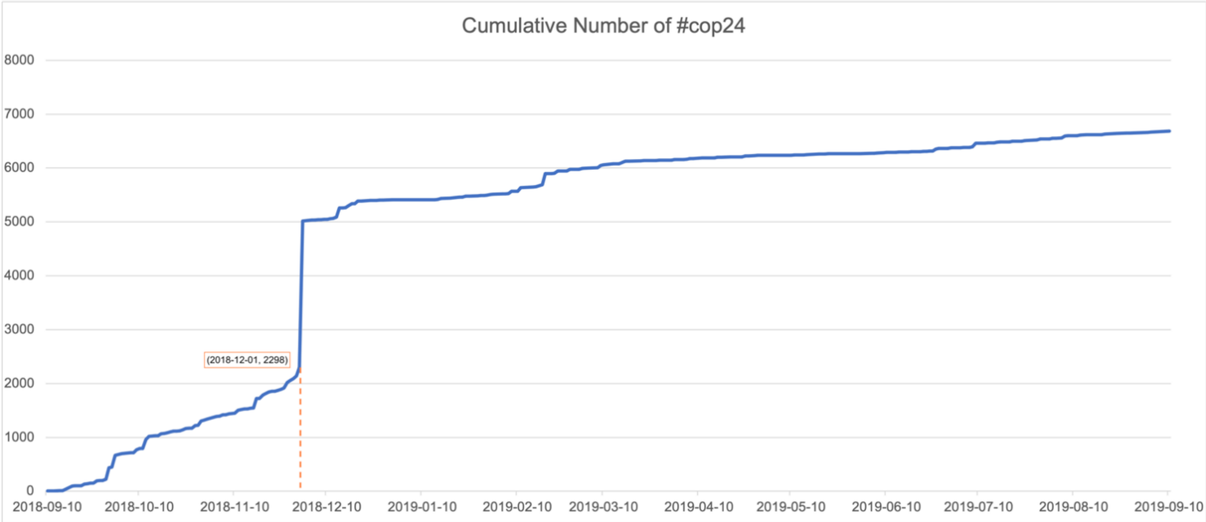

Figure 5-1. Cumulative number of the hashtag #cop24 over the year

5.3.1 Coding of hashtags

Though there are some studies providing coding schemes about climate change, they have typically focused on the frames generated by the editors, elites or politicians, especially on mass media. For example, the widely used typology of frames applicable to climate change summarised by Nisbet (2009) is mainly based on studies about media coverage of climate change. It is different from the frames generated by various users on Twitter, including the general public. As there is no coding scheme in the literature of user-generated hashtags about climate change on Twitter, I made the coding scheme in this chapter based on the literature and the dataset inductively. As for the literature, for example, four thematic clusters about climate change on Twitter have been explored by Veltri and Atanasova (2017): ‘calls for action and awareness of climate change, its consequences and causes, and the policy debate about climate change and energy’ (p. 733), by combining automatic thematic analysis, semantic network analysis and text classification based on more than 60,000 tweets collected using a random week sample. Vu et al. (2021) summarised three elements of strategic framing of climate change: impacts (such as drought or natural disasters), actions (such as specific solutions or mitigation actions) and efficacy (‘efficacy refers to individuals’ perception that a problem is addressable and that they are able to engage in the relevant action needed to address the problem’: Hart and Feldman, 2016, p. 2). According to Vu et al. (2021), little research has explored ‘the presence of these three elements in strategic climate messages’. Efficacy is also emphasised by Hart and Feldman (2016) because ‘efficacy information helps individuals feel capable of overcoming a threat and, in turn, encourages protective action to lessen the threat; if efficacy is low, individuals will instead succumb to fear and engage in defensive mechanisms to control their emotions rather than take action to minimise the threat’

(p. 3). Specifically, I came up with the first-level coding scheme, shown in Table A-1, after bringing up the categories in the literature about climate change science (e.g. National Research Council, 2011). Then, as it cannot cover the whole picture of user-generated content on Twitter, other categories were added based on the frequency of hashtags in specific categories appearing in the dataset. The summary of the results of the first-level coding scheme is shown in

Table A-2. The results were checked thoroughly by another coder (my primary supervisor) with the Cohen's kappa of our intercoder reliability K = 0.887, and the results were also randomly checked by the third coder (my associate supervisor).

The first-level coding was applied to the top 1,000 hashtags, with only 33 hashtags coded as 'Other'. This means that the coding scheme covers most of the prominent hashtags related to climate change on Twitter. As suggested by Shi et al. (2020), excluding hashtags with low frequencies helps us focus on more meaningful rather than occasional associations that are not recognised socially. As the frequency of the 500th most used hashtag was only used 327 times in the whole year, it is reasonable to focus for the network analysis below on the top 500, which are more prominent, rather than the top 1,000 hashtags. To clarify, RQ2a is based on the top 1,000 hashtags, and RQ2b and RQ2c related to hashtag co-occurrence networks are based on the top 500 hashtags.

In the following section, I will introduce how I applied the hashtag co-occurrence network analysis, including categorising the important hashtags into four types according to the network statistics, using MST to visualise the networks, and the application of ERGMs.

5.3.2 Hashtag co-occurrence network analysis

5.3.2.1 Hubs and bridges

Degree is the number of nodes to which a particular node is connected. Betweenness centrality measures the extent to which a node is located 'between' other nodes in the network; in other words, it measures the extent to which a node has the potential to control others as a 'gatekeeper' or 'broker' (Scott and Carrington, 2011). Hashtags with a high degree indicate they are highly used in combination with other co-occurring hashtags, and hashtags with high betweenness centrality play bridge roles between other hashtags in the network.

Shim et al. (2015) introduced a framework to categorise concepts into four different types depending on the degree and betweenness centrality. Following Shim et al. (2015), this chapter categorises the roles of hashtags in the network into four types according to the hashtag's degree and betweenness centrality, as shown in Table 5-1. Hashtags with both high degree and betweenness centrality play the role of global hubs to disseminate meaning across the entire network; hashtags with a high degree but relatively low betweenness centrality play the role of local hubs in the clusters, because they are connected with high numbers of the co-occurring hashtag but other clusters do not rely on them to connect together; hashtags with high betweenness centrality but relatively low degree play the role of bridges, because they are important for clusters to connect together but are not important for their neighbour (Shim et al., 2015). Hashtags with both relatively low degree and betweenness centrality play peripheral roles. But they are not the focus of this chapter.

The idea of Shim et al. (2015) is significant. However, no specific measures are illustrated by them to decide whether degree or centrality is high or low. To apply their framework here, I first ranked nodes according to their degree centrality and betweenness centrality, and I came up with a standard used here, which is shown in Table 5-1.

Table 5-1. Structural types of hashtags by degree and betweenness centrality

	Betweenness	
	High (top 10%)	Low (smaller than 10)
Degree		
High (top 10%)	Global hub	Local hub
Low (outside top 100)	Bridge	Periphery

There were 464 hashtags in Period 1, and 500 hashtags in Period 2. In this chapter, a hashtag with a high degree or high betweenness centrality means the hashtag’s degree or betweenness centrality ranks in the top 10% of all the hashtags. A hashtag with a low degree means the hashtag’s degree ranks out of the top 100. A hashtag with low betweenness centrality means the hashtag’s betweenness centrality is smaller than 10. The detailed lists of global hubs, local hubs and bridges of the two periods are shown in Table A-3 and

Table A-4 in the Appendix.

5.3.2.2 Minimum spanning tree

An MST is a subset network that only contains the minimum number of links that connect all the nodes in the network (Kruskal, 1956; Prim, 1957). The MST has been applied as an economic optimisation method for computing the smallest possible road network in which all places are still reachable from any other places in the network (Ducke and Suchowska, 2021). As stated by Ducke and Suchowska (2021), the MST is 'a useful model for the shape of a network's backbone' (p. 16). Ackland et al. (2020) had already applied it to semantic network analysis to show 'how the hashtags connect to each other semantically and cluster into key areas of public and policy interest'. There are many pairs of hashtags that are not directly connected in the full network. For these pairs, there are shortest paths for them to connect with each other. I use MST to identify these paths, which shows the most efficient ways hashtags are connected, so that the network would be superbly simplified. Not showing all the redundant edges makes the visualisation much clearer and easier to read and test.

5.3.2.3 Exponential random graph models

Social network data consists of *n* actors and a relational tie x_{ij} (i, j = 1, …, n). It is denoted as $x_{ij} = 1$ if there is a relation from actor *i* to actor *j*, and $x_{ij} = 0$ if there is no such relation. The network matrix *X* is a random variable with a sample space of $X \subseteq \{0,1\}^g$, where *g* is the total number of possible ties in a network (Shortreed et al., 2006). ERGMs are the family of distributions that have been most widely applied to model social networks (Lusher et al., 2012). As Cranmer et al. (2017) illustrated, 'the ERGM finds its parameters by maximizing the probability of the observed network over the networks with the same number of vertices that could have been observed' (p. 240). The general form of the model is structured as follows:

$$P(X = x) = \frac{exp\left(\theta' n(x)\right)}{k(\theta)}$$

where *X* is the random variable for the state of the network with realisation *x*, $n(x)$ is the network statistics for *X*, θ is the vector of coefficients for those statistics, and $k(\theta)$ denotes the quantity in the numerator summed over all possible networks.

In other words, ERGMs examine 'the probability of the network we observed over the network we could have observed' (Cranmer et al., 2017, p. 240). When the estimate of a parameter is positive and significant, it reveals that the configuration (i.e. the small network patterns) occurs more often than in a random network given other effects in the model.

ERGMs have been applied by some researchers to the networks filtered by MST, such as Pang et al. (2021), to enable the application of ERGMs on large networks. I apply ERGMs to the hashtag co-occurrence networks refined by the MST to test the backbone structures and compare the features of the two networks in the two periods. Specifically, to test H2, I include the following effects in my model of each period. *Arc* in ERGMs is the baseline propensity to form ties, similar to the intercept in linear regression. Factor attribute effect (*nodefactor* in the R package **statnet**) tells how certain node attributes affect the formation of the network, and uniform homophily and differential homophily (*nodematch* in **statnet**) measures whether nodes with certain attributes tend to connect with other nodes with the same attributes. However, in this chapter I call it ‘assortativity’ rather than homophily because the hashtags are connected by users rather than choosing to connect to each other by the hashtag itself.

5.4 Results

5.4.1 Categories of hashtags

The codebook for the first-level coding, grouping the hashtags into more specific categories such as collective action, weather, and pollution, is shown in Table A-1 in the Appendix. I grouped them as second-level categories, such as consequences, conflicts, and actors, and will analyse the second-level categories from now on. The counts of each category, both the first level and the second level, are shown in

Table A-2 in the Appendix. It is worth noting that I group causes and solutions as one category because both treat climate change as an issue to be solved by analysing what caused the problem and what we can do to solve the problem, rather than relating climate change to social, political or economic concerns.

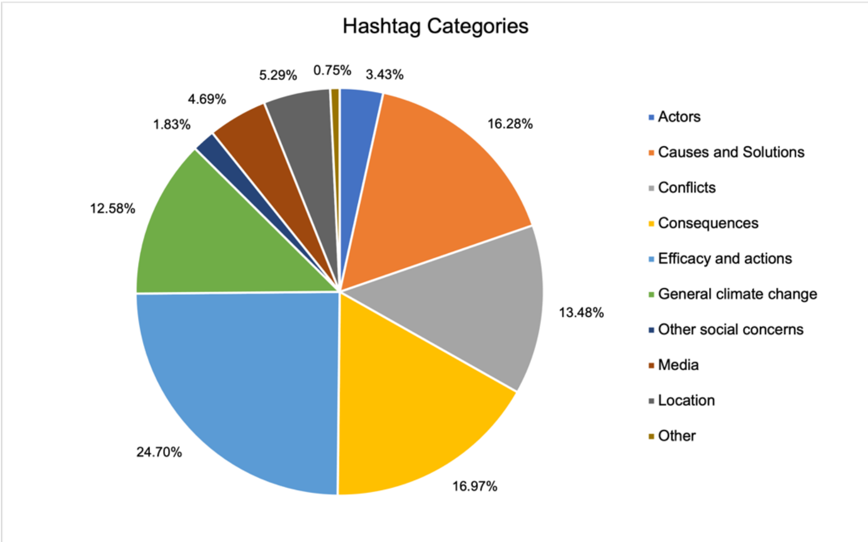

Figure 5-2. The proportions of hashtag categories

We can see from the categories shown in Figure 5-2 that 'efficacy and actions' (24.7%) takes the most significant part of the corpus, followed by 'consequences' (16.97%), 'causes and solutions' (16.28%), 'conflicts' (13.48%), and 'general climate change' (12.58%). 'Other social concerns', such as 'gender', 'ideology' and 'other social issues', only takes a minor part (1.83%).

5.4.2 Important hashtags in the two periods

To clearly show the categories of the hashtags in two periods, I summarise Table A-3 and

Table A-4 in the Appendix in Figure 5-3 and Table 5-2. Figure 5-3 shows the proportions of each category in each period, and Table 5-2 compares the common hashtags and the different hashtags in the two periods at the micro level.

The different proportions of categories in each role shows the importance of different aspects of climate change when users are talking about climate change. For example, ‘consequences’ and ‘causes and solutions’ account for 30.8% and 26.9% of all global hubs in Period 1, respectively, which means that these two aspects of climate change contribute the most to spreading meaning in the entire network, compared to others. These two categories also contribute a lot to spreading meaning in the local neighbours as local hubs in Period 1, but only ‘consequences’ contributes a lot to connecting other hashtags in different communities as bridges. In Period 2, global hubs changed a lot with the increases of ‘efficacy and actions’ and ‘general climate change’, and the decrease of ‘causes and solutions’.

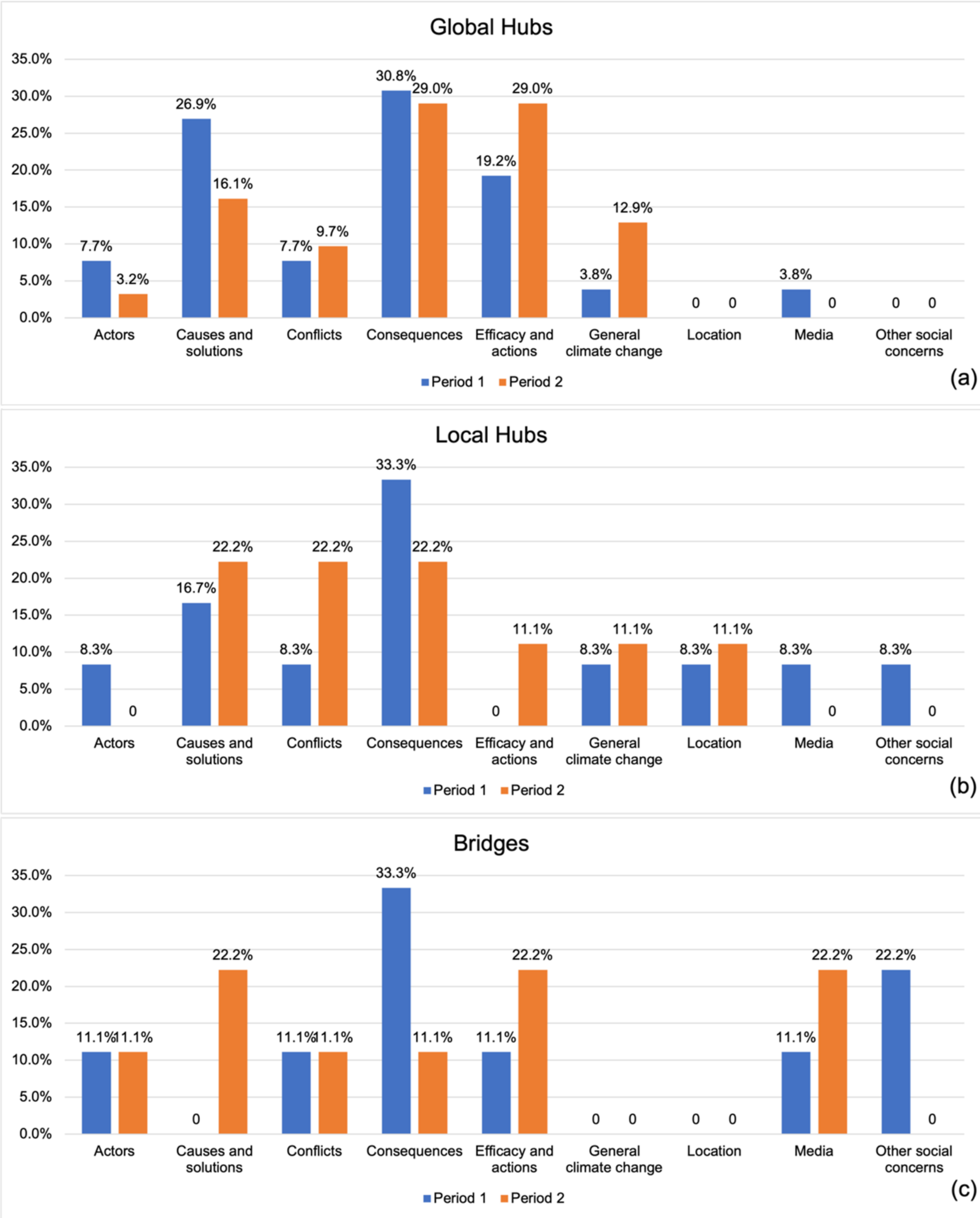

Figure 5-3. Categories of hubs and bridges in two periods

Regardless of the time, there are some overall features of the categories in the three roles. There is no 'general climate change' in bridges; 'locations' are only important as local hubs; 'media' takes a small proportion in global hubs; and there are no hashtags of 'other social concerns' playing as global hubs. When considering time, the roles of 'conflicts', 'efficacy and actions', and 'general climate change' as global hubs are stronger in Period 2, while they are weaker for 'actors', 'causes and solutions' and 'consequences' (slightly). As for local hubs, 'actors', 'media' and 'other social concerns' disappeared, while 'efficacy and actions' appeared in Period 2. What's more, the roles of 'causes and solutions', 'general climate change', 'location' and, especially, 'conflicts' are stronger, and 'consequences' is much weaker in Period 2. In bridges, 'causes and solutions' appeared in Period 2 with a large proportion, while 'consequences' dropped a lot and 'other social concerns' disappeared. Both 'efficacy and actions' and 'media' also became stronger.

Table 5-2. Structural types of hashtags and the comparison between two periods

Global hub	Common in two periods	climateaction, climate, environment, globalwarming, sustainability, energy, actonclimate, nature, water, earth, co2, sdgs, auspol, trump, parisagreement, ocean, cdnpoli, agriculture
	Only in Period 1	science, cop24, pollution, renewables, ipcc, cleanenergy, carbon, coal, drought
	Only in Period 2	climatecrisis, climateemergency, climatestrike, greennewdeal, renewableenergy, health, extinctionrebellion, fridaysforfuture, biodiversity, solar, politics, climatejustice, food
Local hub	Common in two periods	emissions, environmental, green, fossilfuels, weather, canada
	Only in Period 1	un, innovation, economy, future, forests, news, humanrights
	Only in Period 2	climatechangeisreal, climateactionnow
Bridge	Common in two periods	art, vegan
	Only in Period 1	animals, hurricane, cpc, onpoli, hurricaneflorence, security, women
	Only in Period 2	medium, maga, glacier, writer, resist, energyefficiency, buildings

From Figure 5-3, we can see many differences in the usage of hashtags in the two periods regarding the hashtags' structural types. Hashtags of 'general climate change' play the role of global hubs and local hubs in both periods, and the proportions are similar, but do not play the role of bridges in any period. The proportions of 'conflicts' in global hubs and local hubs increased in Period 2, especially in local hubs. The proportions of 'causes and solutions' decreased in global hubs, and increased in local hubs in Period 2. The proportion of 'efficacy and actions' in global hubs and bridges increased significantly in Period 2. 'Efficacy and actions' did not play the role of local hubs in Period 1 but did so in Period 2. 'Media' served as global hubs and local hubs in Period 1 but not in Period 2, and it played the roles of bridges in both periods, increasing in Period 2. 'Consequences' takes the similar proportion in two periods as global hubs, but decreased significantly in local hubs and bridges in Period 2. The proportion of 'actors' decreased in global hubs but increased significantly in local hubs in Period 2, and stays similar in bridges.

We can tell the differences between specific hashtags in the two periods from Table 5-2. Regarding the global hubs, hashtags about specific problems such as pollution, carbon, coal and drought play the role of global hubs in Period 1 but not in Period 2. In Period 2, some hashtags about social movements emerged, such as #extinctionrebellion, #fridaysforfuture and #climatestrike. A similar feature appears in local hubs as well. Some specific concerns about climate change such as economy, future and forests no longer played as local hubs in Period 2, while hashtags about the debate about whether climate change is real and calling for actions for climate became local hubs instead. Regarding bridges, most of the hashtags playing the role of bridges changed in Period 2. This is partly because Hurricane Florence, a specific natural disaster, was significant in Period 1, and users' concern varied into other topics in Period 2, such as #maga ('Make America Great Again') and energy efficiency.

5.4.3 Network statistics of the two periods

Table 5-3. Network-level statistics of co-occurrence networks of the top 500 hashtags

Network-level statistics	Period 1	Period 2
Number of nodes	464	500
Number of edges	14476	37253
Density	0.135	0.297
Diameter	2.234	0.599
Degree assortativity	−0.191	−0.208
Categorical assortativity	0.070	0.037

Density is defined as the proportion of the total number of edges to the number of possible edges in a network (Scott and Carrington, 2011). Though the numbers of nodes in the two periods are similar, the density of the network in Period 2 is 2.2 times the density of the network in Period 1. This reveals that hashtags are connected by much more edges after #cop24 became prominent. The diameter of a network is defined as the longest distance between any pair of nodes, which represents the linear size of the network (Scott and Carrington, 2011). The diameter of the network in Period 2 is only 26.8% of what it had been in Period 1, which shows that the distance between the furthest pair of hashtags in the network was nearer after #cop24 became prominent.

The assortativity coefficient of a graph measures the extent to which vertices with the same properties connect to each other, and ranges between −1 and 1. If the assortativity coefficient is close to 1, two vertices with the same property are very likely to be connected. In contrast, if it is close to −1, two vertices with the same property are not likely to be connected. Degree assortativity is the most common form of numerical assortativity (McNulty, 2022). Degree assortativity close to −1 shows preferential attachment in the network, which means that vertices with a low degree tend to be connected with vertices with high degrees. As shown in Table 5-3, degree assortativity in both periods is negative, and shows slightly stronger preferential attachment in Period 2. Categorical assortativity in both periods is slightly larger than zero, which shows a weak tendency that hashtags in the same category are connected with each other and lower in Period 2. But it is worth noting that the categorical assortativity here can only reveal the overall tendency rather than the category-specific tendency. For example, we cannot tell whether the 'efficacy and actions' hashtags tend to be connected with each other.

5.4.4 Minimum spanning tree visualisation

From the graphs of MST-filtered networks shown in Figure 5-4 and Figure **5-5**, we can find that hashtags #environment (consequences), #energy (efficacy and actions) and #auspol (conflicts) are connected with the hashtags in the same categories with themselves in Period 1. In Period 2, a similar feature applies to #environment and #auspol, but this is less obvious for #energy. The hubs in the MST-filtered network align with the global hubs identified using degree and betweenness centrality from the full (original) network.

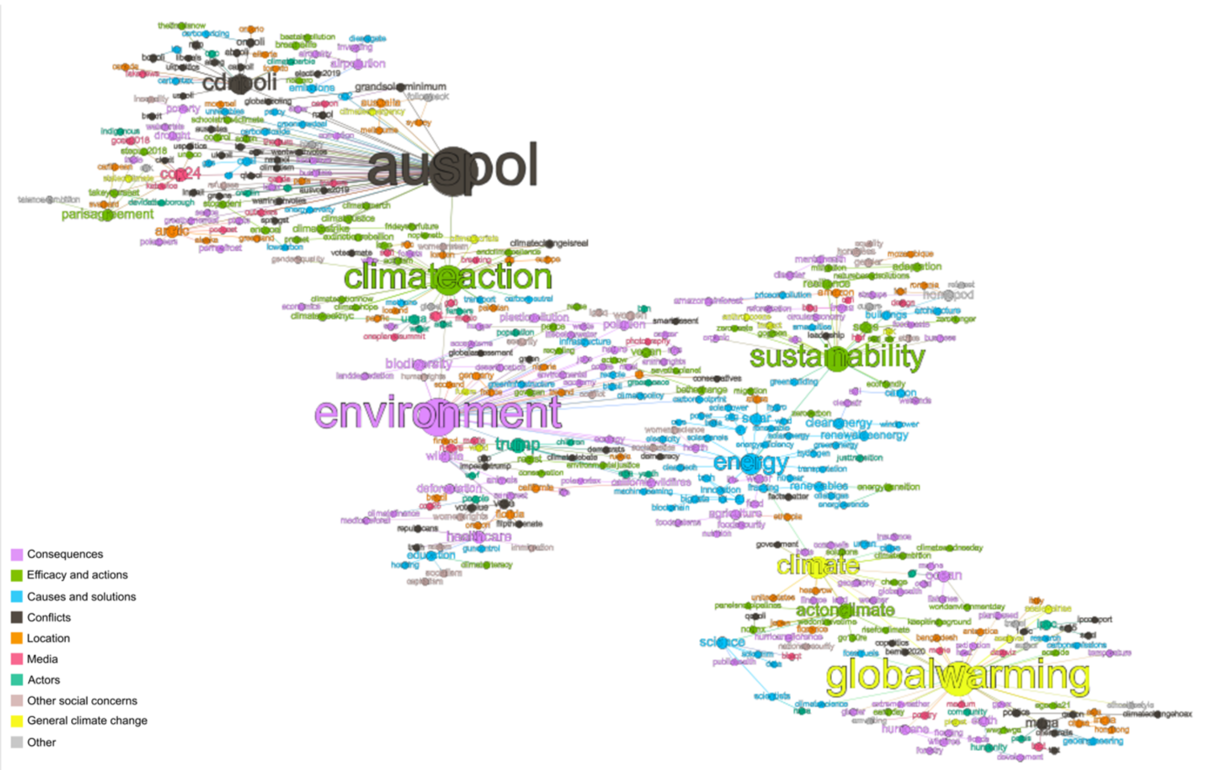

Figure 5-4. MST-filtered hashtag co-occurrence network graph (Period 1)

Note. The graph was generated using the ForceAtlas2 layout algorithm in Gephi.

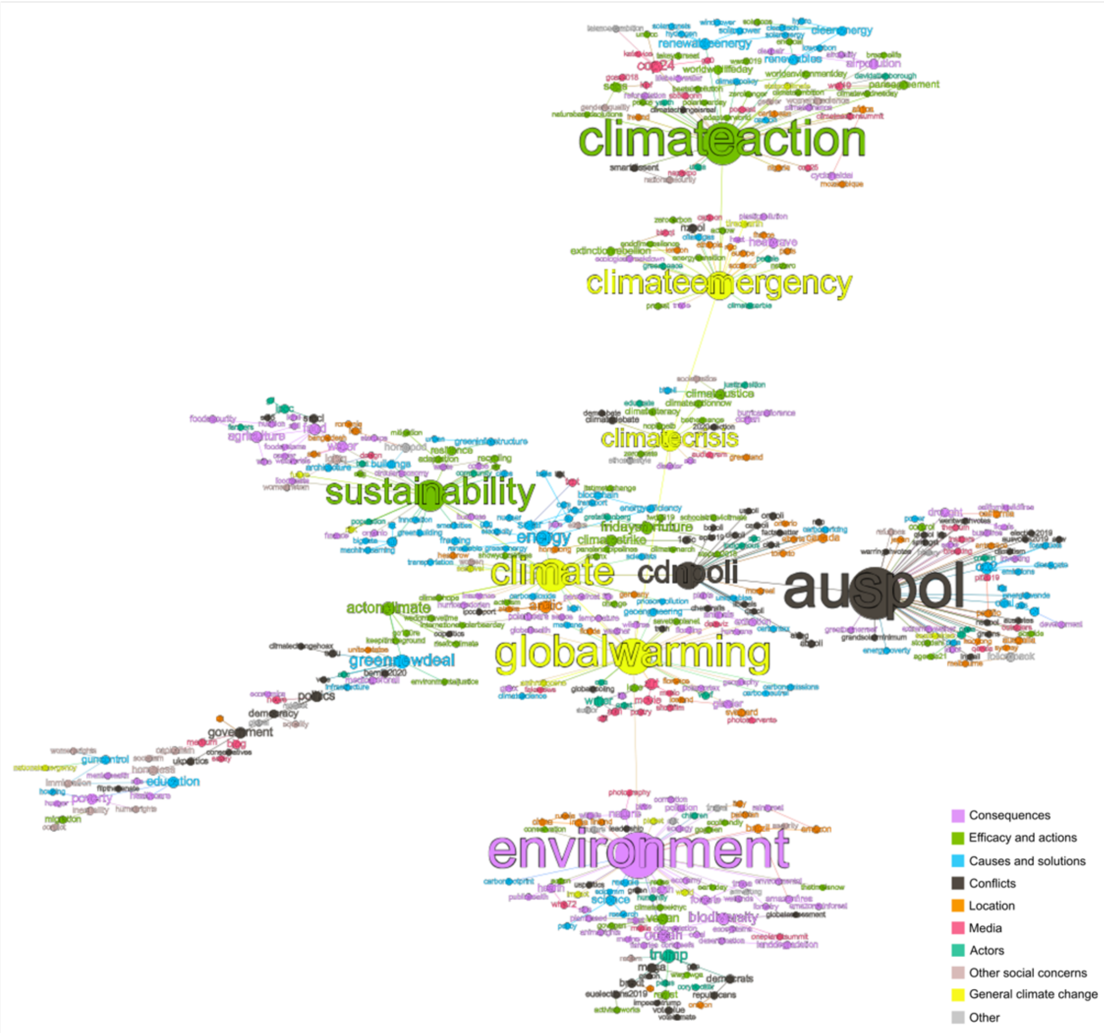

Figure 5-5. MST-filtered hashtag co-occurrence network graph (Period 2)

Note. The graph was generated using the ForceAtlas2 layout algorithm in Gephi.

5.4.5 ERGM

Table 5-4. ERGM results of MST-filtered networks

	Period 1			Period 2		
	Estimate	S.E.		Estimate	S.E.	
Edges	−5.852	0.484	***	−5.958	0.484	***
Factor attribute effect						
Actors	−0.027	0.294		−0.007	0.293	
Causes and solutions	−0.515	0.279	.	−0.355	0.274	
Conflicts	0.080	0.270		0.125	0.268	
Consequences	0.055	0.265		−0.071	0.265	
Efficacy and actions	0.112	0.267		0.301	0.264	
General climate change	1.141	0.279	***	1.621	0.269	***
Location	−0.186	0.281		−0.157	0.280	
Media	−0.316	0.294		−0.123	0.287	
Other social concerns	−0.320	0.329		−0.185	0.320	
Assortativity						
Actors	0.937	0.665		−0.101	1.052	
Causes and solutions	2.602	0.309	***	2.198	0.301	***
Conflicts	1.375	0.289	***	1.519	0.277	***
Consequences	0.788	0.253	**	1.222	0.252	***
Efficacy and actions	1.039	0.277	***	0.664	0.271	*
General climate change	0.044	0.644		−0.087	0.474	
Location	1.159	0.450	*	0.918	0.491	.
Media	0.520	0.780		1.500	0.483	**
Other social concerns	2.258	0.730	**	1.684	0.822	*
	AIC: 5910 BIC: 6095			AIC: 6245 BIC: 6430		

Significance levels: *** 0 < p < 0.001; ** 0.001 <= p < 0.01; * 0.01 <= p < 0.05; . 0.05 <= p< 0.1

As shown in Table 5-4, the negative estimates of *Arc* in each month show that the networks tend to be less dense than random networks. As for *factor attribute effects*, estimates of ‘causes and solutions’ in Period 1 are significantly negative, which means hashtags related to causes and solutions of climate change tended to be harder to connect with other hashtags, while this is no longer significant in Period 2. ‘General climate change’ is significantly positive in both periods, which reveals that it is easier for hashtags related to general climate change to be connected with other hashtags in the network. When it comes to assortativity, most categories have significant positive coefficients in both periods, except ‘actors’, ‘general climate change’ and ‘media’, which means that hashtags of most categories had the tendency to be connected to other hashtags in the same categories in both periods. The coefficient of ‘Media’ became significantly positive in Period 2, which means that hashtags related to media did not tend to be connected with other hashtags related to media in Period 1, but tended to be so in Period 2.

5.5 Discussion and conclusion

This chapter has examined the deliberative process of collective sense-making of climate change on Twitter through hashtags. Specifically, I studied the frame articulation and frame amplification processes, as introduced in Section 5.2.1. Taking COP24 as a significant event over the year (September 2018 to September 2019), I looked into how the collective framing of climate change on Twitter changed in the aftermath of COP24 through answering three subquestions. By answering RQ2a (What kinds of hashtags were selected to talk about the topic of climate change on Twitter?), we can get an overall sense of the elements of the climate change problem that Twitter users selected to frame climate change as a political issue, which is the outcome of frame amplification. To answer RQ2a, I manually categorised the hashtags that users posted in tweets with #climatechange. Given the lack of coding schemes of hashtags related to climate change on Twitter, I followed some frames in climate change-related research, combining with the ones from hashtags inductively. To refine the large number of detailed categories for the complicated climate change topic, I first got the first-level categories, and grouped them into the macro-categories by using manual coding.

From the coding results, I found that users most often selected hashtags about efficacy and actions, which shows a positive signal that users are confident about the ability to tackle climate change or are expressing hope and care about taking actions for it, regardless of the existence of uncertainty. Users are also concerned about the consequences, as well as causes and solutions of climate change. Efficacy and actions, consequences, causes and solutions reflect the key tasks of 'collective action frames' that Benford and Snow (2000) argued: 'diagnostic framing', 'prognostic framing', and 'motivational framing', as introduced in Section 5.2.1. This reveals that climate change tends to be framed as an issue requiring collective actions. Specifically, users tended to use diagnostic framing to identify the causes of climate change, for example transportation and carbon emissions. They used prognostic framing to articulate proposed solutions or alternative arrangements, such as energy supply and use, and climate policies. They also applied motivational framing to mobilise actions, such as circulating intergovernmental initiated plans (e.g. the IPCC report) and promoting social movements (e.g. climate strikes).

To examine the frame articulation process, I explored the important hashtags in the hashtag co-occurrence networks (RQ2b), which reveals the outcome of frame articulation, and the tendency of how different hashtags are connected with each other (RQ2c), which shows the details of frame articulation process.

Through users' collective frame articulation, hashtags of 'consequences' and 'causes and solutions' are the most significant global hubs in spreading meaning in the entire network, especially in Period 1. However, in Period 2, 'efficacy and actions' take the most significant proportion in global hubs, as do 'consequences'. This reveals that users tend to use hashtags of 'efficacy and actions' to help spread meaning in the entire network, instead of 'causes and solutions' after COP24. Similarly, in local hubs and bridges, 'efficacy and actions' also increased a lot in Period 2, from which we can conclude that users rely more on 'efficacy and actions' in frame articulation after COP24. Hashtags of 'consequences' took the most significant proportions in all the three important roles in Period 1, but a much smaller proportion in bridges in Period 2, which shows that users relied less on hashtags of 'consequences' to connect various hashtag communities. When we explore the specific hashtags playing the three roles in the two periods, the most interesting finding is that after COP24 users tended to use hashtags about social movements as global hubs and local hubs, such as #ClimateStrike, #ExtinctionRebellion, and #FridayForFuture as global hubs, and #climateactionnow as a local hub. It reveals that users try to frame climate change as an issue that needs changes and actions after COP24. Further studies can investigate what specific hashtags the bridges are connecting.

From the network statistics of hashtag co-occurrence network, I found weak preferential attachment phenomenon and categorical assortativity in both periods. This reveals two stable features in climate change framing on Twitter: (1) users connect less popular hashtags with more popular hashtags and make the latter even more popular, and (2) users tend to connect the hashtags in the same category together in general. To explore more details about (2), I applied ERGMs to the MST-filtered network to test the assortativity at the specific category level. It turns out that the assortativity was relatively stable in the two periods. Hashtags of most categories tended to be connected to the hashtags of the same categories with themselves, except for 'general climate change' and 'actors'. Regarding 'general climate change', we can infer that users tended to connect the general topics of climate change with other more specific topics rather than with other general topics. The visualisation of the MST-filtered networks helps us to understand the structure of the hashtag co-occurrence network in a more efficient and clearer way than showing the full network. The common hashtags playing the role of global hubs in both periods shown in the graphs reveal that these are related to the dominant frames about climate change on Twitter throughout the year.

It is a limitation of this chapter that we cannot conclude that the changes in the two periods were completely brought about by COP24. However, as COP24 was an important event during the year, the changes are correlated to it to some extent. What's more, by comparing the two periods, we can identify some stable and consistent features (including some variances) of the framing in the year about climate change on Twitter.

From this chapter, we learned that users participated in deliberation by collectively framing the topic of climate change on Twitter. Users selected and associated different hashtags in multiple ways, and the framing tended to be more problem-solving oriented after COP24. And now we turn to my final case, which focuses on different user groups' framing of the emerging technology of negative emissions.

Chapter 6 User Groups' Collective Framing of Negative Emissions on Twitter

6.1 Introduction

As discussed in Chapter 2, climate change is, as scholars such as Levin et al. (2012) and Kahane (2018) have noted, an ongoing 'super wicked problem' that is complicated and poses significant threats to people around the world. As illustrated in previous chapters, social media can help us understand how people frame issues that can provide insight into the broader public discourse. Unlike news media, where journalists select and edit content, social media offers unfiltered raw information generated by the wider public themselves on any topic (Spierings et al., 2018). Content generation by lay users and 'amateur activity, by those who may have authentic knowledge and information access' are at the heart of social media such as Twitter (Klinger and Svensson, 2015, p. 1247). Although there are massive discussions of climate change on social media, the role of social media in communicating emerging and less-known climate-related technical and environmental topics, such as negative emissions, has not been well studied (Kim and Cooke, 2018). This chapter argues that, rather than only looking at climate change as a whole, it is valuable to focus on emerging subtopics related to climate change, to know how these topics are currently communicated, examine the deliberation in the communication of emerging issues, and then prevent or solve possible communication problems that have occurred in the topic such as political polarisation. By looking at who talks about each of these climate change subtopics and how different user groups frame the topic collectively, this chapter explores the deliberation in which different user groups engage on Twitter. The research question of this chapter is: RQ3. How did different user groups on Twitter collectively frame negative emissions via tweets? I will answer this through two subquestions: RQ3a. Who is talking about negative emissions on Twitter? RQ3b. How did different user groups collectively frame negative emissions from 10 June to 10 September 2019?

In comparison to Chapter 5, which explored hashtags as a political technology for the users as a whole to participate in the collective framing, this chapter takes tweet text as the data to analyse, and focuses on the collective framings of different user groups. Alongside the traditional content analysis method to categorise user groups, I apply structural topic modelling (STM), an unsupervised machine learning technique, to analyse the frames embedded in tweets, which is very time-consuming for traditional content analysis and requires manual coding for categorisation. The data analysed in this chapter covers the period 10 June 2019 to 10 September 2019 (93 days), which is relatively a short period regarding big data, but it does contribute to the application of structural topic modelling in climate change communication, or even online communication about other political issues.

6.2 Background

6.2.1 Negative emissions as an emerging technological topic

Climate change is ‘a problem of cumulative greenhouse gas emissions, amassing in the atmosphere at a rate that exceeds their reabsorption and/or degradation through geological, biological and chemical processes’ (Carton, 2019, p. 757). Researchers in climate science have been working on restricting the emissions of greenhouse gas, such as carbon dioxide (CO_2), to mitigate climate change, but – as many researchers such as Nekuda Malik (2019) and Minx et al. (2017) have argued – that appears likely to be insufficient. The adoption of additional strategies like the large-scale removal of CO_2 from the atmosphere has been identified as a potential pathway to climate change mitigation, and this process of drawing down CO_2 is known as negative emissions (NE) (Fuss et al., 2014; Minx et al., 2017). NE first received lasting attention in the early 2000s (Buck, 2018). The climate change mitigation scenarios of the IPCC (Intergovernmental Panel on Climate Change) have come to rely on NE to meet the 2°C/1.5°C temperature targets of the Paris Agreement (Schleussner et al., 2016), which indicates the idea that ‘climate change can no longer be addressed merely by reducing emissions, but that it will require the removal of vast amounts of carbon from the atmosphere as well’ (Carton, 2019, p. 750).

NE technologies may be attractive from certain economic perspective, because they ‘allow higher total carbon emissions, and/or a later peak in emissions’ (Gough and Vaughan, 2015, p. 2), and hence appear to be promising for transitioning to a low-carbon economy (Meadowcroft, 2013). However, what NE promises does appear to require ‘the massive and widespread deployment of technological systems with heavy, capital-intensive infrastructure that has not been proven at scale’ (Buck, 2018, p. 1). Carton (2019) takes Shell, a fossil fuel company, as an example to illustrate why these companies are including NE in their development scenarios. According to Carton (2019), Shell expects that ‘carbon dioxide removal will be rapidly scaling up, and that by 2070 the world will have reached “net-zero emissions” through the large-scale deployment of carbon capture and storage (CCS) and NETs, primarily BECCS’ (p. 760), which actually ‘allows any real efforts to be deferred until after 2030 and therefore allows Shell to gradually diversify/alter its business model despite the urgency of climate change’ (p. 760). NE remains in its infancy with respect to scalable solutions (Smith et al., 2016). Besides the ‘unveiled areas of uncertainty’ in NE literature, there is a need to understand better the barriers to the implementation of NE and how these can be overcome (Fuss et al., 2018, p. 34).

One technology more favoured by scholars to deploy NE is called 'bioenergy with carbon capture and storage' (BECCS) (Smith et al., 2016), which is 'a so far commercially unproven proposal to combine the cultivation of bioenergy crops (which, like all plants, sequester carbon from the atmosphere through photosynthesis) with their combustion for energy generation, and the capturing and long-term geological storage of the resulting CO_2 emissions' (Carton, 2019, pp. 750–751). However, the land area required to implement BECCS sufficient to counter carbon emissions is around 7–25% of the planet's total agricultural land (Williamson, 2016), which is likely to cause conflicts over land use, biodiversity conservation and food production (Buck, 2018), and would increase demands for freshwater and fertiliser use (Minx et al., 2018).

Scholars are already concerned that the NE concept has already been playing a political role (Carton, 2019), primarily because 'negative emissions help to pre-empt a crisis of political legitimacy by seemingly answering calls for ambitious climate action, all the while deferring the most difficult questions to the future' (Carton, 2019, p. 759). The above example of Shell also reflects researchers' concern about the 'moral hazard' related to NE. The concept of moral hazard comes from economics, and it refers to a situation where 'there is perverse incentivization of risky behaviour' (Lenzi, 2018, p. 2). For example, an actor might have an incentive to expose themselves to more risks because the actor knows its insurance will pay for the costs. NE has been called 'an unjust and high-stakes gamble' (Anderson and Peters, 2016, p. 183). According to Lenzi (2018), '[n]egative emissions can be a valuable means of limiting dangerous climate change, or an unjust gamble against the future'. NE might be a mitigation obstruction to some near-term mitigation. On the other hand, NE can also become a convenient excuse for policymakers to delay near-term mitigation (Lenzi, 2018). The large-scale deployment of NE cannot avoid engaging the public and different social groups. But all of the literature discussed to this point is based on what scientists and researchers say, and more needs to be done to understand what the wider public is saying about NE.

Thus, while work clearly needs to progress on the technological front, more needs to be done in understanding how they interact with social factors relating to acceptance and public attitudes (Buck, 2016; Minx et al., 2017; Colvin et al., 2019). Exploring and understanding these social factors can also help provide a bigger picture for policymakers and decision-makers (Fuss et al., 2014). This is yet to be a focus area as Nemet et al. (2018) identified that the literature around NE technologies is still situated in the research and development phase, and it is relatively marginal within the broader climate change discourse (Minx et al., 2017), let alone research specifically on communication about NE. Given the intrinsic connections between NE and climate change, Colvin et al. (2019) argued that NE could become caught up in a social-political complexity similar to climate change, potentially resulting in a similar political polarisation (Hornsey et al., 2018). What's more, it is crucial to choose the right communication strategy for NE, because there are already studies showing the negative effects of focusing on recent progress in NE: it improves people's sense of hope regarding climate change, with payoffs of weakening mitigation motivation (e.g. Hornsey and Fielding, 2016). This highlights the importance and demand of exploring how NE is conceptualised socially to aid in communication and provide a broader picture of NE for policymakers (Fuss et al., 2014).

Recent studies about climate change on Twitter show that climate change has been discussed by users from different groups, including NGOs, grassroots activists, scientists, politicians and celebrities (e.g. Anderson, 2011; Lück et al., 2016; Walter et al., 2019). But who is talking about NE on Twitter? This is the first research question of this chapter. People with different backgrounds talk to others with their own understanding about the topic, as well as with their ideological stances, and frame the topic for their own interests related to their social positions. For example, somebody who is running a company using carbon dioxide removal techniques to make profits may express ideas or diffuse information more beneficial to her business. When multiple users pursuing similar interests come together to express their ideas, it makes certain frames salient. When we focus on different groups of users and compare their frames in the same period, it can reflect how they collectively frame NE.

Rapidly developing machine learning techniques and natural language processing enable us to manage large datasets of text. In correspondence with Chapter 5, this chapter also looks at collective dynamics framing, but, in a departure from Chapter 5, this chapter zooms in on user groups' collective framing, and analysing the full text from their tweets, including hashtags, rather than only focusing on hashtags. In this chapter, I categorise Twitter users into groups according to their professions and affiliations, and identify different user groups' frames through the tweets they post.

6.2.2 Structural topic modelling

In traditional social sciences, researchers manually code text data to infer the features of texts. To do this, 'theory-based categories and coding schemes are first created, and coders are trained accordingly. Then, the coders or raters read through the text under analysis with the coding scheme in mind, which functioned like a rake gathering leaves from a forest floor, to deduce targeted categories or constructs' (Kim et al., 2020). To ensure that the codes measured are reliable, the interrater agreement of the coding is measured by a coefficient, such as Cohen's kappa (Cohen, 1960). In Chapter 5, I applied a modified traditional method when coding the hashtags by generating coding schemes both based on literature and the data collected, because no coding schemes of user-generated hashtags related to climate change exists. I will also apply this method in this chapter when coding user groups. The traditional method works well with a relatively small dataset, but when it comes to large datasets, such as data on social media, the demand for resources, such as the time required for coding, will increase significantly. To overcome this limitation, automatic text analysis methods of classification have been developed, and this set of methods can be divided into two camps depending on whether there are predefined categories. According to Grimmer and Stewart (2013), classification based on known categories consists of two approaches: the dictionary method and the supervised learning method. The dictionary method is similar to the method of manually coding with predefined categories by researchers, but different because the coding is conducted by computers. In the supervised learning method, 'the data set with known categories are divided into a training set and a test set prior to model building. The training set is used to build an optimal model in which a combination of features is identified to best predict the target feature. Then, the model is evaluated and validated on the test set' (Kim et al., 2020, p. 65).

Unlike the camp of methods with known categories, the unsupervised learning method, including topic modelling, classifies texts into unknown categories, and discovers these latent categories or topics based on word co-occurrences across documents (Grimmer and Stewart, 2013).

Topic models are developed in the interdisciplinary domains of machine learning, statistics and computational linguistics (Kim et al., 2020). Topic modelling is an unsupervised machine learning technique that detects word and phrase patterns within documents, and clusters word groups and similar expressions automatically that best characterise the documents (Grun and Hornik, 2011). Topic modelling can generate lists of the important words to a topic, the most important topics within a corpus, and the topics that can describe the entire corpus. Researchers interpret and label the topics after getting them using topic modelling. One of the most important assumptions of the most common types of topic models is the 'bag-of-words' assumption, which means that 'the order of words in a document is irrelevant, and language particularities such as syntax and grammar can be ignored' (Lesnikowski et al., 2019). The other important assumption is that the number of topics in the corpus is fixed, which is denoted by the letter K. As stated in many papers related to topic modelling (e.g. Roberts et al., 2019; Pandur et al., 2020), selecting k is vital in topic modelling and requires interpretation from the researcher. An advantage of topic models is that a document can belong to several topics. For example, a tweet in topic models can comprise 10% of Topic 1, 60% of Topic 2, 20% of Topic 3 and 10% of Topic 4, if there are four topics in total. Therefore, topic models are more flexible than traditional mixture models that assign each document to a single topic (Blei et al., 2003). Lesnikowski et al. (2019) suggested that topic modelling is particularly valuable in exploratory research when 'researchers are interested in discovering unknown patterns or trends in the data or are seeking external validation of inductively determined categories'. From this perspective, it is a very promising method for studies like this chapter that focus on new topics without existing coding schemes.

Latent Dirichlet allocation (LDA) (Blei et al., 2003) was 'the first, widely used topic model that provided a foundation to the ensuing topic models' (Kim et al., 2020, p. 66). Dirichlet here means the Dirichlet distributions in probability and statistics, which is commonly used in Bayesian statistics. As illustrated by Vayansky and Kumar (2020), 'LDA regards documents as generated from randomised mixtures of hidden topics, which are seen as probability distributions over words' (p. 3). In other words, each document (e.g. a tweet) is distributed over topics, and each topic is distributed over words. Structural topic modelling (STM) is built upon LDA (Blei et al., 2003) but compensates for some limitations of LDA. First, STM incorporates covariates that can take advantage of metadata collected with text data, which provides important information about each text (Roberts et al., 2016), such as the author's demographic information or the time when the text was generated. Second, unlike LDA assuming topic independence, STM allows the correlation of topics, which is more realistic because some topics often occur in the same group of documents (Roberts et al., 2016).

One challenge in the unsupervised learning method is that the number of hidden topics is not readily observable and must be estimated. STM also shares this challenge. Following Kim et al. (2020), I combine four criteria of model diagnostic statistics from the literature to ease this challenge: held-out likelihood (Wallach et al., 2009), semantic coherence (Mimno et al., 2011), exclusivity (Bischof and Airoldi, 2012) and residuals (Taddy, 2012). A topic model fits better than other models when it has higher held-out likelihood, semantic coherence and exclusivity and lower residuals. The held-out likelihood refers to 'the probability of unseen held-out documents given some training documents' (Wallach et al., 2009, p. 2), and it is 'calculated from the test set and conceptually analogous to a fit index of a confirmatory factor analysis model on a second data set after the model has been identified with an exploratory factor analysis model on the first data set’ (Kim et al., 2020, p. 68). The semantic coherence assumes that the high-probability terms of a topic tend to occur across documents and assesses the optimal number of topics that provides the most semantically coherent topics (Mimno et al., 2011). The exclusivity requires that high-probability terms should be unique and exclusive to one topic rather than overlap with high-probability terms in other topics (Bischof and Airoldi, 2012). It is closely related to semantic coherence, as an exclusive and coherent topic tends to be more interpretable and meaningful. The residual reflects the variance between the true number of topics and the current number of topics. If a residual is larger than 1, the former is larger than the latter.

Although there are several studies that have discussed the applications of topic modelling in social science (e.g. Grubert and Algee-Hewitt, 2017; Wilkerson and Casas, 2017), topic modelling, let alone STM, has not been well explored in online deliberation and climate change literature. Only a few researchers have applied STM to framing analysis. For example, Stelmach and Boudet (2021) utilised structural topic modelling to examine the use of collective action frames and the dynamic of framing in the comments at public hearings and letters to the editor in local newspapers (N = 4618) over the 16 years that a proposal about liquefied natural gas infrastructures was under consideration. I demonstrate here that STM’s ability to analyse large volumes of text contributes important insights on online discussions of NE and uncover the framing strategies used by the public. This can shed light on how NE is framed among users on Twitter, as well as how it is framed differently between different user groups.

Lynam (2016) applied topic modelling and Bayesian networks to analyse the social representations of adapting to climate change in different social groups, namely government employees, members of the public, and researchers. The data source of Lynam’s (2016) study was collected from three separate occasions (people attending an international scientific symposium on climate change, people working in an Australian state government department related to climate change, and people working on climate change in Canada and residents at the eastern seaboard of Australia) with the help of an online survey instrument. It is more feasible to analyse different social groups using surveys, because researchers can tell participants’ demographic features from surveys or even target the group first before conducting the surveys. However, in the case of Twitter data, missing information and fake information exist, which makes it difficult to distinguish users’ social groups. Instead, I take ‘user groups’ to loosen the restrictions, and categorise the groups using their bio-information shown on their Twitter profiles.

Besides distinguishing user groups' framing, I will also assess who the frames changed over time, particularly during the period 10 June to 10 September 2019. The second research question is: how did different user groups collectively frame negative emissions from 10 June to 10 September 2019?

In sum, the research questions of this chapter are as follows:

> RQ3a. Who is talking about negative emissions on Twitter?
>
> RQ3b. How did different user groups collectively frame negative emissions from 10 June to 10 September 2019?

6.3 Data and methods

6.3.1 Data

I collected publicly available Twitter data (ANU ethics number: 2019/325) via the Twitter API (https://developer.twitter.com/en/docs/twitter-api) using NodeXL Pro (Smith et al. 2010), which is an add-in for Microsoft Excel to collect social media data. Before data collection, I built up a list of terms relating to NE through a survey to assist with data collection. The survey was administered to 48 authors who had published academic articles on NE, from whom 13 responses were received. The authors were asked what other words or terms came to mind when explaining or discussing NE. Based on their responses, the search terms I used to collect Twitter data were: 'CO2 removal', 'greenhouse gas removal', 'carbon sequestration', 'CO2 sequestration', 'carbon management', 'carbon drawdown', 'carbon capture', 'CO2 capture', 'blue carbon' and 'negative emissions'. As I focus on original content posted by users, retweets and replies were excluded. After extracting tweets in English, there were 6,182 Twitter users who posted 8,524 tweets related to NE in the time frame from 10 June 2019 to 10 September 2019 (93 days).

6.3.2 Method

6.3.2.1 User geographical distribution

To explore potential geographical factors, I also collected geographic information based on users' biographical information. There is no requirement for users to show their geographical information on Twitter, but 3,715 out of the total 6,182 users still made it available. I classified their locations into countries by VBA programming in Excel. The results are shown in Figure 6-4.

6.3.2.2 User groups

As there are no existing coding schemes in the literature for categorising Twitter users engaged in NE, I used the collected dataset to inductively construct a codebook for classification (see Table 6-1). Specifically, I first classified 100 random users based on the biographical information presented on Twitter profiles separately with a collaborator, a Ph.D. candidate who is versed in climate communication issues to get users' initial categories. After discussing the results, another random sample of 100 users was coded against this codebook separately until an adequate agreement was reached. This coding exercise was repeated three times, with the last Cohen's kappa of our intercoder reliability K = 0.957, which reached the so-called 'near-perfect agreement' (Viera and Garrett, 2005).

Table 6-1. Coding schemes for categorising user groups

User group	Definition
Government (G)	Anyone working in the government sector, including the EU, UN, and their sub-organisations.
Academia (A)	Anyone working in academia, which means research, university teaching, academic publishing, policy analyst, journal editors, think tanks, academic conference/forum, etc.
Media (M)	An account that is news media-focused.
NGO (N)	Anyone working in organisations that are not for profit, including NGOs, charities, foundations, associations, memberships, etc., as long as their purposes are not for profit.
Business (B)	Anyone working in companies or for-profit organisations or doing farming.
Other (O)	Anyone who cannot be sorted into the above categories.
NA	Missing data (blank), non-English bios, or incomprehensible information.

6.3.2.3 Structural topic modelling on tweets

Within this analysis, a 'word' will represent the fundamental unit of analysis, a 'document' refers to a tweet, and a 'corpus' refers to the whole dataset containing all the tweets. I pre-processed tweets with the R package **quanteda** before applying STM. In this pre-processing, words that are connected by hyphenation were split into words and hyphenation-like characters. Punctuation, symbols, numbers, URLs and stop words are all excluded. Hashtags are kept, as users also used hashtags to express their ideas or preferences. The remaining words in the text of the tweet were converted to lowercase letters. To better understand the content, the words were not stemmed when creating the document-feature matrix for modelling. For example, ‘working’ was not stemmed to ‘work’. The structural topic models were estimated by R package **stm**.

6.3.2.4 Number of topics

K represents the desired number of topics from structural topic modelling. As I discussed above, it is always challenging to decide which K to choose, as there is no completely right answer (Grimmer and Stewart, 2013). Selecting K has not been best explained in the literature. I decided K based on the current research. According to Lindstedt (2019), ‘[g]iven the difficulties associated with model selection and the trade-off between predictive and interpretable models, the ultimate responsibility for model selection rests with the researcher and their informed judgment’ (p. 310). There are two solutions suggested by Roberts et al. (2019) for selecting a better K. The first is, from among several Ks given by the user, selecting a K according to held-out likelihood, residual, semantic coherence, and lower bound, as introduced above. The other is, based on the algorithm by Lee et al. (2014), using the spectral initialisation with K = 0 to automatically select the number of topics using a random seed. I combined the two solutions together to find the K for the corpus in this chapter. First, with ten different random seeds for spectral initialisation with K = 0, I got seven different numbers of topics ($K_1 = 40$, $K_2 = 43$, $K_3 = 47$, $K_4 = 48$, $K_5 = 50$, $K_6 = 52$, $K_7 = 55$). Then I selected K based on the criteria shown in Figure 6-1, from which I excluded $K_5 = 50$, $K_6 = 52$, and $K_7 = 55$, because these models obviously have either lower held-out likelihood, larger residuals or lower semantic coherence. However, it was still hard to select from $K_1 = 40$, $K_2 = 43$, $K_3 = 47$ and $K_4 = 48$. Then I turned to the average exclusivity and semantic coherence. Exclusivity measures the proportion of the top words that are exclusive to the topic, and semantic coherence is a frequency measure that prioritises the works in a topic co-occur (Mimno et al., 2011; Roberts et al., 2014). The results are shown in Figure 6-2. The more topics in the top-right quadrant, the better the model works from the perspectives of exclusivity and semantic coherence. There are 45.0% ($K_1 = 40$), 53.5% ($K_2 = 43$), 46.8% ($K_3 = 47$) and 45.8% ($K_4 = 48$) of all the topics in each model, respectively, located in the top-right quadrant. $K_2 = 43$ does a relatively better job than others. Therefore, the number of topics K in the model is 43.

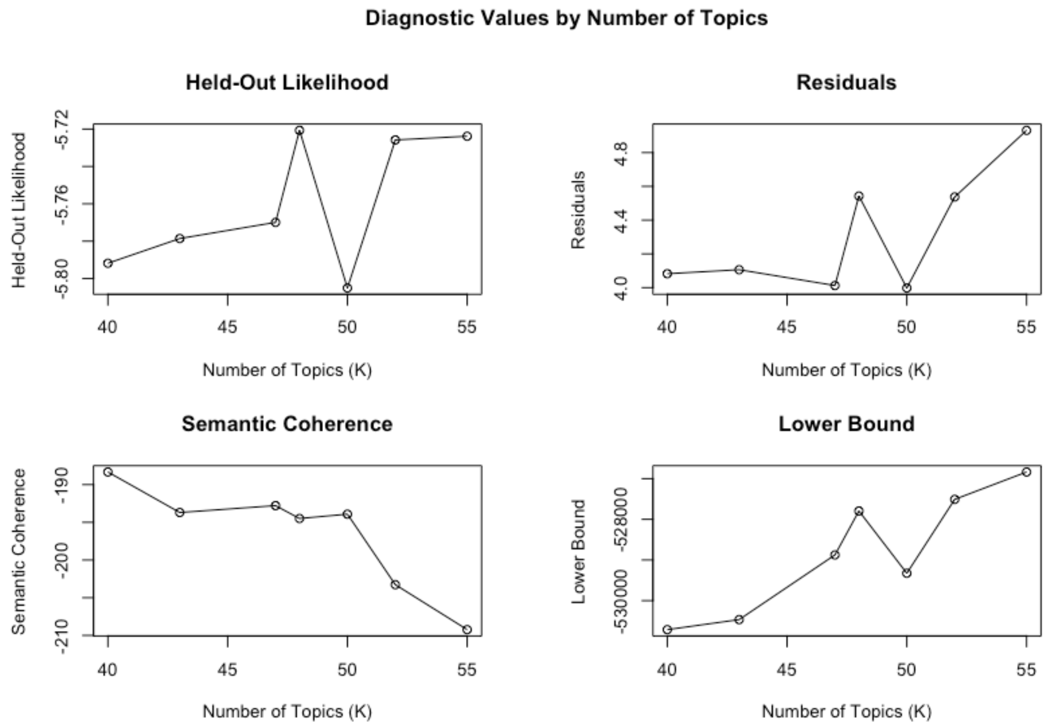

Figure 6-1. Diagnostic values by number of topics

Figure 6-2. Exclusivity against semantic coherence

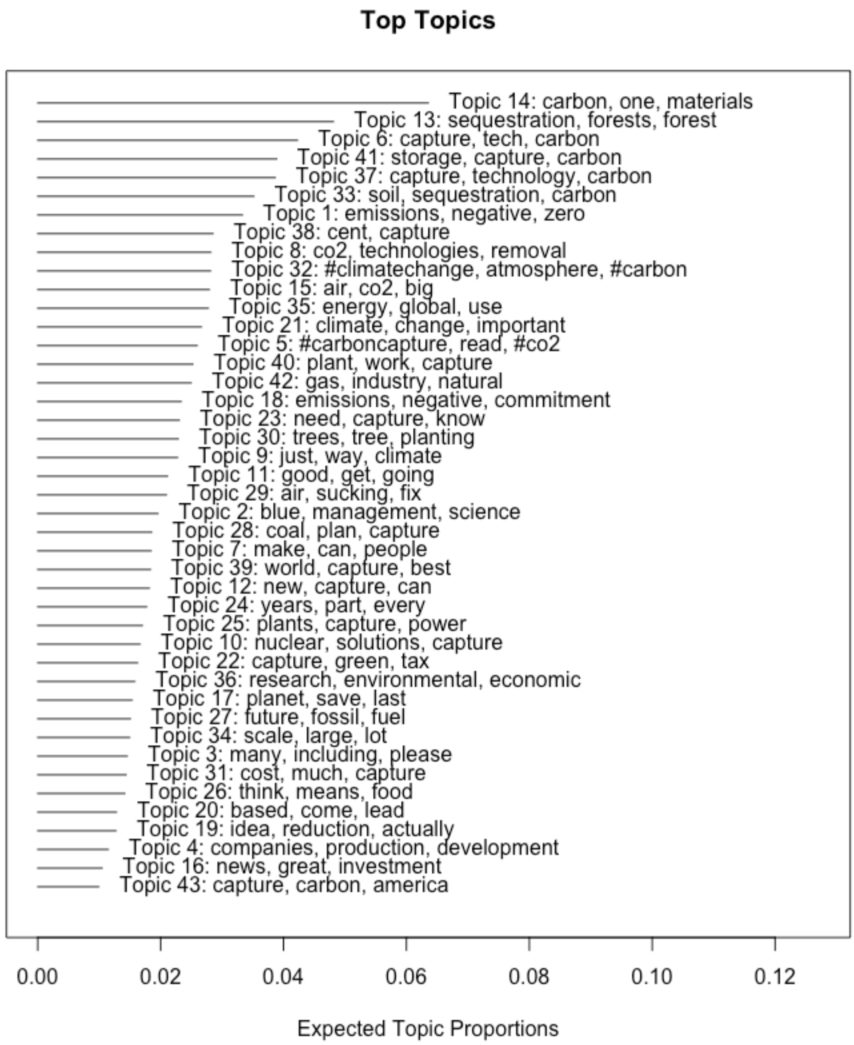

Figure 6-3. Expected topic proportions (K = 43)

The 43 machine-generated topics from the corpus are shown as words with expected topic proportions (Figure 6-3), which cannot be taken as topics directly and required further human interpretation. Separately, I and the collaborator versed in climate communication qualitatively interpreted the topics according to these words and representative tweets, and then we discussed to refine the results (Table A-5). Specifically, we interpreted the topics according to the highest-probability words, FREX words, lift weights words, and scores, combining the tweets that are highly associated with topics. As Roberts et al. (2019) defined them, 'FREX weights words by their overall frequency and how exclusive they are to the topic', 'lift weights words by dividing by their frequency in other topics, therefore giving higher weight to words that appear less frequently in other topics', and 'score divides the log frequency of the word in the topic by the log frequency of the word in other topics' (p. 13). As there are many similar ones in the 43 topics, we grouped them into frames, with specific labels. For details, see the Appendix. One of the strengths of STM is the inclusion of document-level metadata, so that we can reveal which kind of users are more active in a certain frame. User types engaged in every frame over time are shown in Figure 6-6, which will be illustrated in the Results section. The expected topic proportion means the expected proportion of the corpus that belongs to the topic. '[T]he sum of the topic proportions across all topics for a document is one' (Roberts et al., 2019, p. 2). Figure 6-6 shows the effect of the time variable (day) on the expected topic proportions, which therefore reveals the topic prevalence, with 95% confidence intervals.

6.4 Results

6.4.1 Users' geographical distribution

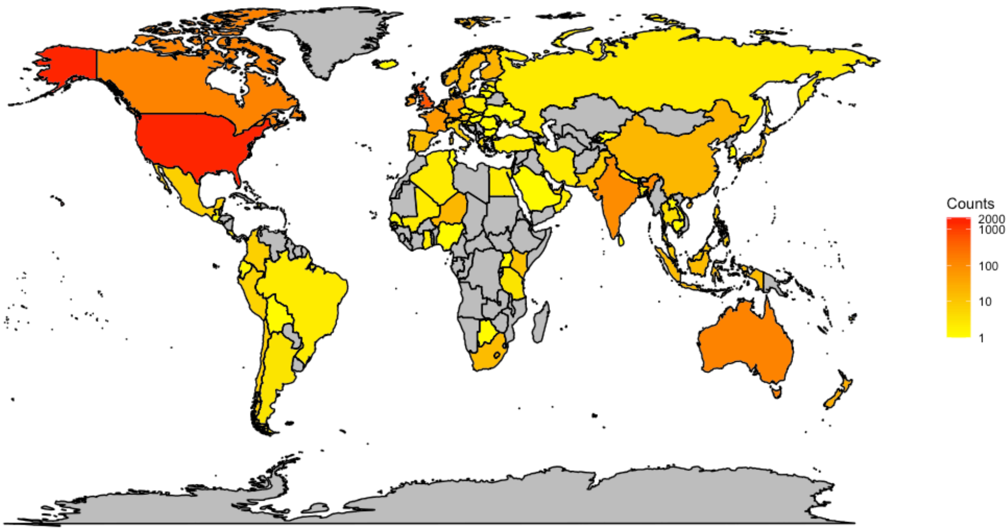

Figure 6-4. Users' geographical distribution

The colour in Figure 6-4 is darker if more Twitter users in that country talked about NE using the keywords. According to the geographical distribution, we can find that the United States led the discourse about NE on Twitter, with 2,106 users, which constituted 56.7% of the available data. Following the United States, the United Kingdom and Australia also contribute more to the discourse than other countries, with 576 and 141 users, respectively. However, it is worth remembering that only around half of users (3,715 out of 6,182) had available geographical information and their tweets are in English, from which the exploration of the geographical distribution is limited.

6.4.2 User groups

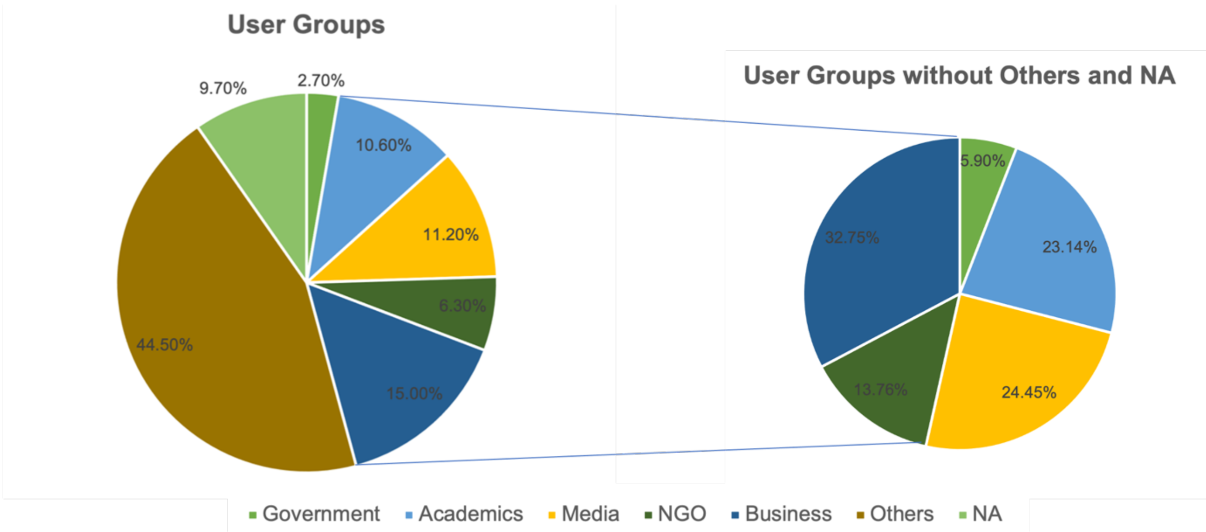

Figure 6-5. The composition of user groups

Except for user accounts with no information for categorising (i.e. 'NA') and user accounts that are not of interest of this chapter (i.e. 'Others'), the configuration of users who tweeted about NE in the 93 days is shown in Figure 6-5. Business takes the most significant part (32.75%), followed by media (24.45%), academics (23.14%) and NGOs (13.76%). Accounts that are from governments take the smallest part (5.9%).

6.4.3 Frames from topic modelling

The topics that emerged in the discourse can be grouped into seven frames: general support, uncertainty/doubt, natural solutions, political support, the role of business, the role of the fossil fuel industry, and scientific/technological progress. The definitions of the identified frames are listed in Table 6-2. The details with frames interpreted from the keywords in each topic are shown in the Appendix. Table 6-3 presents an example showing how Topic 11 is assigned to the frame 'Uncertainty/doubt' based on the keywords identified with the topic and representative tweets.

Table 6-2. Definitions of the identified frames

Frame	Definition
General support	The topic shows positive support to NE, e.g. regarding NE as a solution to mitigate climate change, or promoting the promise of NE.
Uncertainty/doubt	The topic shows doubts about NE, e.g. mentioning possible side effects of NE.
Natural solutions	The topic focuses on the role of natural solutions or shows preference to natural solutions rather than promoting the deployment of NE.
Political support	The topic focuses on the role of politicians, governments or funding from governments in NE.
The role of business	The topic focuses on specific companies or businesses related to NE.
The role of the fossil fuel industry	The topic focuses on the relationship between the fossil fuel industry and NE.
Scientific/technological progress	The topic focuses on the scientific advancement or technological development of NE.

Table 6-3. Keywords and representative tweets for interpreting Topic 11

Keywords	Highest prob: good, get, going, stop, want, keep, go FREX: keep, get, right, want, stop, going, good Lift: simple, jail, card, try, keep, multiple, right Score: simple, good, keep, get, going, stop, go
Representative tweets	There is no get out of jail free card for #ClimateEmergency https://t.co/4jbZglHUsP Negative emissions technologies, are they a get out of jail free card allowing us to keep emitting and clean up the mess later? https://t.co/PaGB5BOxUq Unpopular opinion of mine: We should stop concentrating on going to Mars let alone going back to the moon and instead focus those efforts on carbon capture. Negative emissions are treated as a get out of jail free card - a licence to keep emitting and clean up the mess later with new technologies. That's why politicians and their advisers love them https://t.co/1fEq5Ts315

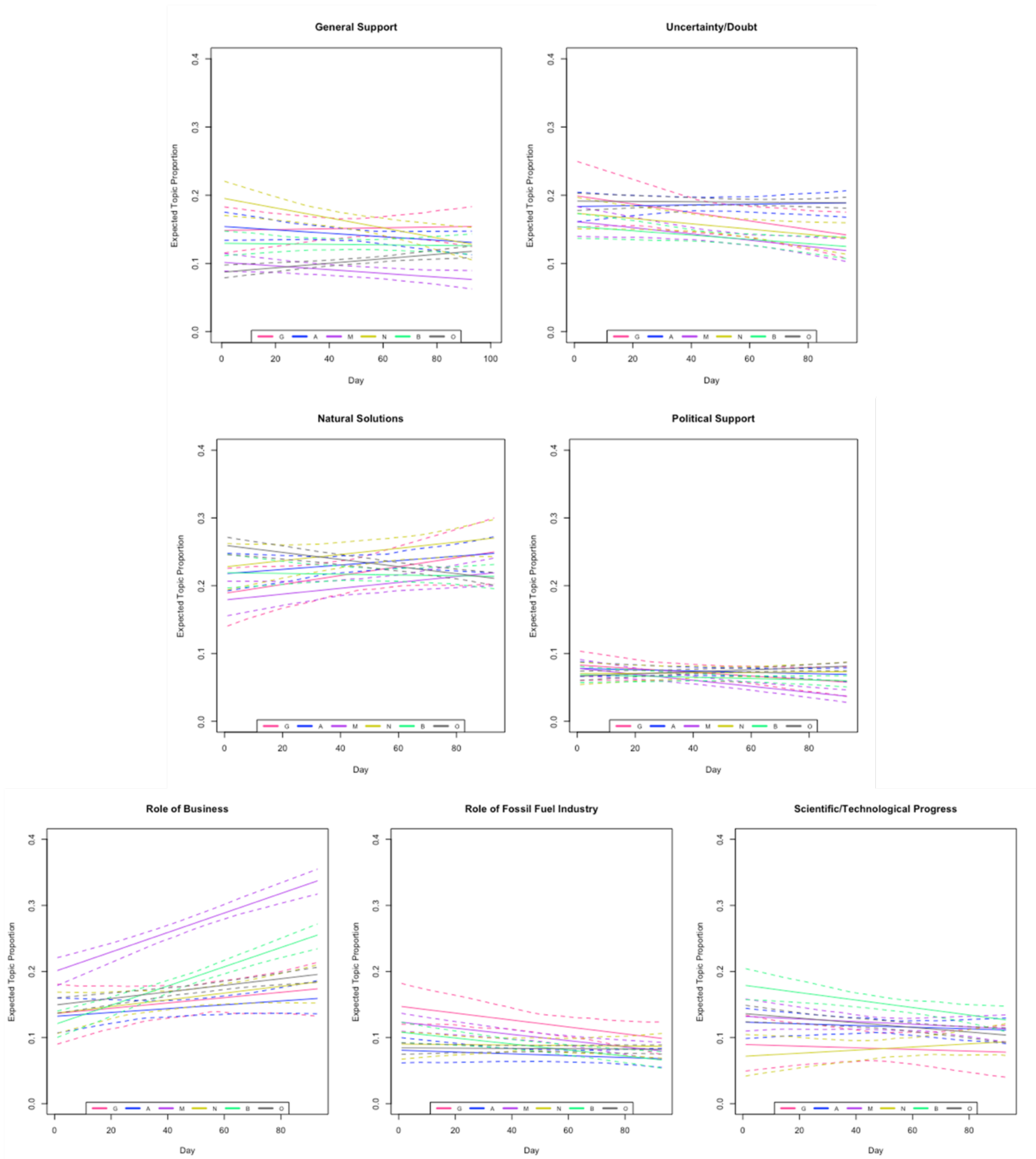

Figure 6-6. The expected topic proportion of each user group in different topic clusters

Note: The solid line denotes the trend of the expected topic proportion of the frame in the user group, and the associated dotted line in the same colour shows the error margins. For example, the proportion of the general support frame in the NGOs group starts from around 20% on Day 1 and ends at around 13% on Day 93.

Having found the existence of the different groups and different frames, I then analysed the evolution of the groups in each frame over time. To evaluate the proportions of each group in each frame, I used the *estimateEffect* function of the **stm** package in R (Roberts et al., 2014), which regresses the proportion of each group in each frame on a frame-specific covariate, i.e. day. It is worth noting that the proportions of each group across all the frames on a given day is one. In other words, when a group expresses more about one frame, it would express less about other frames.

If we compare the expected topic proportions across frames in Figure 6-6. The expected topic proportion of each user group in different topic clusters, we find that natural solution was the most popular frame (most of the proportions are around 20% or more) across most of the user groups, and political support was the least (most of the proportions were less than 10%). Under this trend, most of the groups had their largest proportions in natural solution and minimum proportions in political support. However, the media had a more significant proportion in the role of business, while playing a minor role in the natural solution. Compared to other groups, governments paid the least attention to scientific/technological progress, and academics paid the least attention to the role of the fossil fuel industry.

As for each frame, general support was promoted mainly by NGOs with a decreasing trend, and governments with a stable trend over time, while it lost the media’s attention. Academics argued the most in uncertainty/doubt frame with a stable trend, while other groups showed decreasing interest, especially governments. The media and business were less likely to express uncertainty/doubt. NGOs were the most prominent group in the natural solution frame, and showed slightly increasing interest; again, media and business showed minor interest. But all the groups showed slightly increasing interest in the natural solution frame, except ‘Others’, which is not the interest of this chapter. In the role of business frame, media paid the most attention, and this rapidly increased during the 93-day period. We can also find a significant increase in the business group in this frame. In contrast, in the role of fossil fuel industry frame, almost all the groups showed decreasing interest, even governments, which showed more interest than other groups. In the scientific/technical progress frame, business showed the most interest, but this was decreasing. Governments and NGOs did not pay much attention to this frame, although there was a slight increase in NGOs.

6.5 Discussion and conclusion

This chapter has presented an analysis of the collective framing of NE by different user groups on Twitter. The diversity of user groups talking about NE on Twitter and the diverse frames used by them show that there is a broad range of actors discussing varied topics on Twitter. This is related to the diversity in Chapter 4 that I used to measure the deliberation potential. The diversity in Chapter 4 is structural, while the diversity here is from the perspective of actors and content, and it shows that the discourse about NE on Twitter satisfies one of the conditions for deliberation. To answer the first research question, about who is talking about NE on Twitter, I first analysed the users' geographical distribution and categorised the users into different groups. The users from the United States make up 56.7% of the users who made their geographical information available, while the second and the third countries (the United Kingdom and Australia) take 15.5% and 3.8%, respectively. The dominant role of users from the United States in the discourse of NE on Twitter during the period reflects that, as emerging technologies, NE has mainly been talked about in the United States. There might be some biases because the tweets analysed in this chapter are all in English, and there are more users from the United States in general (in 2022, 25% of users who access Twitter daily were based in the United States, according to https://backlinko.com/twitter-users). As mentioned previously in this chapter, there are no existing coding schemes for categorising user groups about NE on Twitter, I conducted the categorisation in an inductive way, and the users are categorised into business, government, academics, the media, NGOs and others. If we only focus on the first five groups, we can find that business plays a significant role in the discourse of NE, which has not been a focus of climate change communication yet, because the researchers are more interested in user groups such as NGOs, politicians and activists. This reveals the speciality of NE communication. Even though it is still an emerging technological topic, we can see from the results that NE is not a topic that stays in academia. Companies or businesses are especially interested in NE, which is probably because it is a new field for profits. This suggests that NE represents a pathway for businesses to maintain key components of their existing business models and to delay the near-term actions for mitigating climate change. NE also has already caught the media's attention. But, unlike climate change, there are not many users from NGOs in the NE discussion on Twitter. This reflects that NE is not a topic of concern for social movement actors, and fewer NGOs with strong opinions or stances have been engaged in this topic yet. It shows the need for NGOs to prioritise this so as not to cede the discussion to business in the near future.

To answer the second research question, looking into how different user groups collectively frame NE in the period, I applied the structural topic modelling on the pre-processed corpus generated from tweets about NE, interpreted and grouped the topics into frames. I identified seven frames from the corpus: general support, uncertainty/doubt, natural solutions, political support, the role of business, the role of the fossil fuel industry, and scientific/technological progress. Among these frames, natural solutions, uncertainty/doubt, the role of business and general support are the dominant frames in the NE discourse on Twitter in the period. In the natural solutions frame, users tended to twist the mitigation direction to rely on natural solutions rather than NE, which shows users' hesitance to accept NE as a solution to climate change. In comparison to the natural solutions frame, which shows users' preference for alternative solutions, the uncertainty/doubt frame emphasises more strongly the shortcomings of NE. For example, some users doubted whether carbon capture and storage technologies might emit more CO_2 when they are used to capture CO_2. There were also users who raised the moral hazard in NE (Topic 11), which is to delay near-term actions. Despite the preference for natural solutions and doubts about NE, there are still lots of users, especially from NGOs, who support NE generally, feeling hopeful and positive about the promise of NE technologies. This aligns with the argument of Lenzi (2018) that NE still has the possibility of becoming 'a valuable means of limiting dangerous climate change' (p. 1). When comparing the frames of different user groups, I found that media focused more on the role of business, together with the 'business' group, and even more in the predictive future from the trend shown in Figure 6-6, while these two groups played minor roles in the natural solution frame and uncertainty/doubt frame, and an even smaller role in the future in the uncertainty/doubt frame. This finding reveals that, rather than emphasising the alternative natural solutions or the conflict ideas about NE, the media tended to discuss the role of business in NE more.

When we compare the roles of the business frame and the role of the fossil fuel industry frame, an interesting finding is that the role of business is more salient than the role of the fossil fuel industry. This finding is more obvious in governments, business and the media. For example, the expected topic proportion of the role of business frame increased from 20% (which is already much higher than other groups) to more than 30% in the media, while the proportion of the role of fossil fuel industry decreased from around 12% to below 10%. This might reveal that governments, business and the media avoid mentioning the fossil fuel industry specifically to avoid raising conflicts and doubts. However, academics have raised the issue of the uncertainty of the topic and criticised the possible existence of moral hazard.

This chapter contributes to the methodological development in various ways. First, I applied structural topic modelling, an unsupervised learning method, to analyse the frames from short texts (i.e. tweets), which provides social science researchers with an example of how to explore the frames of political issues or even other issues on Twitter. Second, the way I chose a more appropriate number of topics (K) in the topic model is also a good example for researchers who find it too difficult to decide on the K. Third, I applied both the traditional manual coding method and automatic text analysis in the same study, which shows the flexibility of social media research.

However, there are also some limitations in this chapter. First, the sampling method and the platform I chose might lead to biases in the results. There are some countries, such as China and North Korea, that have blocked Twitter and these countries are not covered in this study. Further, I only analysed tweets in English, and the results cannot tell us how users posting in other languages talked about NE. Second, the period I randomly selected is relatively short. It would be more interesting to see the trend over a longer time frame. These represent options that can be adopted in future studies. Also, some topics from the topic modelling were difficult to interpret (for example, Topics 16 and 20), even with the help of typical tweets in the topics. This reveals another methodological limitation.

Chapter 7 Discussion and Conclusion

This chapter summarises the thesis as a whole. Specifically, I seek to introduce the overall purposes; to summarise the main findings and contributions of each case study in Chapters 4, 5 and 6; to review the limitations of my approaches with an eye to evaluating their reliability, limitations and overall effectiveness; to discuss the implications of this thesis; to recommend what can be done for future research; and to give a conclusion for the whole thesis.

7.1 Purposes

Regardless of the existence of many different definitions of deliberation and camps of deliberation studies, many scholars have pointed to the potential positive benefits of deliberation to political issues, such as climate change. However, the majority of the scholarship on deliberation has focused on offline events, such as mini-publics and political institutions, as mentioned in Chapter 2. The boom of the Internet has raised different opinions on the democratic potential of the digital space, of which the representative two camps are the 'cyber-optimists' (Davis, 1999) and the 'cyber-pessimists' (Janssen and Kies, 2005). With the rising role of social media in our social and political lives, how it has influenced democracy and deliberation has been debated in academia, and it is becoming increasingly relevant to figure out whether forms of deliberation manifest in informal communication in online political spaces. I have argued in this study that the rapid advance in online deliberation research requires a more consistent definition and corresponding operationalisation of measurements of online deliberation to guide us do empirical research and examinations. Instead of worrying too much about the side effects of the social media, I have argued that we should focus on the positive influence and utilise it to solve issues which requires wider engagement of the publics.

This thesis has sought to provide insights into the potential of online deliberation from user-generated content on Twitter, and to help further comprehend the features of the communicative practices in the digital space. For this purpose, I emphasise the informal discursive aspect of deliberation, and define online deliberation as the informal online discursive process in which participants express their opinions and discuss with each other with the potential goal of achieving mutual and collective understanding about political issues, following Kim and Kim (2008), Graham (2009) and Dahlgren (2018).

To achieve the goal of examining the potential of online deliberation empirically, I have used the discussion of climate change as a case study. As a complicated, wicked and troublesome political issue, climate change requires the engagement of the general public. It is far from enough to rely solely on governments and other institutions or authorities. According to Black et al. (2008), deliberation makes it possible to raise the bar in citizens' assessment of the complex issue of climate change and help to change the conditions under which the issue could be governed and citizens' expectations in a democratic system. As Niemeyer (2014) suggested, the general public can be attuned to environmental complexities through deliberation and be able to reflect on the issue with a long-term view. Taking climate change as a case study, this thesis has sought to examine the nature of online deliberation in climate change communication on Twitter. In practice, I first examined the discussion networks from the perspective of structure. Specifically, in Chapter 4 I examined the impacts of climate strikes on the deliberative potential of climate change discussions on Twitter using network analysis. I then explored the collective framing in user-generated content in Chapter 5 and Chapter 6. I defined framing as a strategic action whereby individuals select some aspects of issues and make them more salient in communication, and regard the content that users generated together as the outcome of collective framing. In Chapter 5, I explored the processes of frame amplification and frame articulation processes in users' collective framing via hashtags. In Chapter 6, I focused on an emerging technological issue in climate change, negative emissions (NE), and examined its collective framing by different user groups.

Apart from the above purposes, i.e. contributing to a consistent definition and corresponding operationalisation of measurements of online deliberation, examining the potential of online deliberation from the discussion structures and user-generated content, I also sought to make methodological contributions by applying computational social science techniques to online climate change communication studies.

7.2 Findings and contributions

In Chapter 4, I investigated and operationalised the measurements of deliberation in a structural manner to answer how the climate strikes impacted the deliberative potential of climate change discussions online (RQ1). Specifically, I tested two hypotheses: climate strikes raised the visibility on Twitter of the issue of climate change; climate strikes increased the deliberative potential of climate change discussion networks on Twitter. By examining the impacts on online deliberation in climate change discussions brought by the social movement climate strikes, I found that, although there is no simple answer to the deliberative potential of the discussions, climate strikes increased the potential for deliberation by increasing reciprocity and diversity; however, the movement did appear to decrease it regarding equality. In more simple terms, this means that users tended to have further discussions with their discussion partners when talking about climate change after climate strikes, rather than demonstrating opinions in a unidirectional manner. More users became engaged in the discussion, which increased the possibility of the exchange of various ideas. These findings can be taken as positive impacts of the climate strike movement (and perhaps of social movements in general) on the deliberative potential of online discussion. It is significant for solving the climate change issue because, through more deliberative discussions, it is more likely that the plurality of environmental values can be effectively assessed and considered in the decision-making process (Warren, 1996). I also found that the large number of newly joined participants brought more attention to superstars, rather than shared attention from superstars, which increased the inequality of the discussion. However, it might be too narrow-minded to conclude that the presence of superstars and their strengthened roles after social movements are harmful to climate change: scholars such as Boykoff and Goodman (2009) have stated the positive impacts of celebrities in raising public awareness and social movements to forcing climate policy changes. Chapter 4 contributed to measuring online deliberation in a structural approach and providing evidence of positive impacts of social movements on online deliberation. What’s more, the chapter provides an example for other researchers to apply the Gini coefficient and Lorenz curve, which have been applied to measure inequality for income and wealth distributions, to measure and visualise the equality in online discussion networks more accurately and concretely.

In Chapter 5, I argued that collective framing as seen in hashtag co-occurrence networks can be taken as a deliberative process and explored how users collectively framed climate change via hashtags (RQ2). I examined the frame amplification process by exploring what hashtags users selected to communicate about climate change, and the frame articulation process by testing how users associated hashtags related to climate change. Taking COP24 as a remarkable event, I also investigated the changes of the framing before and after the event. I found that after COP24 users tended to rely more on hashtags expressing efficacy and actions and less on hashtags about consequences, causes and solutions, and conflicts of climate change in frame articulation. It shows a positive signal that users are confident about the ability to tackle climate change and tend to express hope and care about taking actions for it, regardless of the existence of uncertainty. In other words, users were trying to frame climate change towards an issue that we are able to – and should – take action on, rather than mainly trying to raise others’ awareness via framing it as an issue causing problems. This is an interesting and meaningful finding because it can give us, and decision-makers and environmental activists especially, confidence about the positive trend in online climate change communication. The exploration of the frame articulation process reveals more about users’ strategies. Users tended to associate less popular hashtags with more popular hashtags to help the diffusion of less popular hashtags that serve their personal purposes, and associate hashtags with the same categories together in many cases to group the similar topics together. Combined with the visualisation, it also shows that there are some dominant frames about climate change throughout the year. Complementary to frequency-based results in examining framing amplification, structure-based results of articulation confirm that hashtags related to efficacy and actions were also used to spread meaning in the network, and this role was strengthened after COP24. These findings show that, instead of randomly including hashtags in tweets, users tended to use hashtags strategically, and confirm that hashtags can be treated as frame makers. This can provide evidence for researchers to justify why they intend to analyse the framing via hashtags. By analysing hashtag co-occurrence networks, this chapter provided an example of how to analyse roles of different hashtags in communication on Twitter. This chapter also contributed to applying inferential network analysis, such as ERGMs, to analyse online data. Superior to descriptive network analysis, such as density and centralities, ERGMs help us to understand how and why network ties arise. In practice, it enables researchers to test hypotheses and find evidence for the tendencies in the network formation process.

In Chapter 6, I looked into different user groups talking about NE and the frames they generated (RQ3). The results indicate that, as an emerging technological topic, NE has been mainly talked about in the United States and has caught lots of interest from businesses, the media, NGOs and governments, rather than just academics. The engagement of companies and businesses is a double-edged sword. It can certainly promote and disclose this technical topic to the wider public. However, we can also see the evidence both from the literature and different user groups' frames that promoting NE can be taken as a pathway for businesses to maintain key components of their existing business models and to delay actions to mitigate climate change. The frames reveal various concerns of different user groups and give us clues to the current situation of the communication and acceptance of NE. For example, the hesitance of users to take NE as a solution to climate change requires more clarification from scholars and decision-makers. The findings in this chapter are significant and meaningful in multiple ways. Having been argued by several scholars recently, such as Buck (2016), Minx et al. (2017) and Colvin et al. (2019), while work clearly needs to progress on the technological front for NE, more needs to be done in understanding how it interacts with social factors relating to acceptance and public attitudes. Exploring and understanding these social factors can also help provide a bigger picture for policymakers and decision-makers (Fuss et al., 2014). My findings help them to explore and understand the acceptance and public attitudes towards NE, and to consider the social impacts of technologies of NE. It is also helpful for communicators to choose the right communication strategy by proving evidence about the status of communication of NE among the public. What's more, this chapter reveals research opportunities for other scholars to focus on certain user groups to study why they choose certain frames and the impacts on the deployment of NE. Colvin et al. (2019) expressed their concern that NE could become caught up in similar social-political complexity as climate change in general, potentially resulting in similar political polarisation. Though my findings cannot directly reveal the presence of polarisation in the discourse about NE on Twitter, it is clear that different users frame NE differently with different trends. Other studies can identify the political stances first and use structural topic modelling to analyse their frames to examine the political polarisation.

In sum, this thesis found evidence of the deliberative potential of online discussions from users' interactions and their collective framing in climate change communication on Twitter.

7.3 Limitations

As with the majority of studies, the design of the current study is subject to limitations. The primary limitation to the generalisation of these results is that, as only tweets in English have been kept for the analysis in this thesis, the findings cannot be taken as inherently representing content posted in other languages. In other words, the politics of climate change explored in this thesis is largely pan-Anglo politics.

The data collection process, which I started to conduct in 2018, leads to three limitations. First, when I collected Twitter data related to climate change, I used the single hashtag #climatechange. I could have also combined with other hashtags, such as #globalwarming. Second, climate strikes occurred after I started to collect data, and I decided to look into this social movement later on. This meant that I only obtained data related to climate strikes when users posted hashtag #climatestrike together with #climatechange. I could have been more sensitive and started to collect #climatestrike separately when the social movements started. Third, the dataset of Chapter 6 about NE only covers three months, from which we can only find limited changes and clues about the evolution of frames. The data collection period could have been extended.

The data clean process results in two limitations. The first limitation is that I excluded all the content that was not in English. Because of this, the findings in this study only reflect pan-Anglo climate change politics. The second is the exclusion of emojis from tweets in Chapter 6. In Chapter 6, by 'tweets', I only meant the textual content and excluded all the emojis. Scholars such as Karthik et al. (2018) have stated that emojis have a significant impact on the opinion that tweets deliver along with the text. However, owing to the limitation of the structural topic modelling, I excluded all the emojis from tweets in Chapter 6. More studies are needed to work out how to combine structural topic modelling with meaning extraction from emojis.

There is also a limitation concerning the measurements of deliberation. In Chapter 4, I only measured the deliberative potential using reciprocity, equality and diversity. Although the way that Schneider (1997) operationalised quality is not suitable for Twitter, I was unable to measure quality in the present dataset. More work could be conducted on this in the future.

7.4 Implications

The implications of the findings in Chapter 4 are threefold. On the theoretical level, it contributes to the empirical definition of online deliberation, which can guide researchers in empirical works. On the empirical level, the methods I applied provide an unambiguous operational way to measure the deliberative potential of online discussions, especially on Twitter, which will allow us to quantify the extent to which the given discussion is deliberative. It can also be used to track the discussions as they evolve over time and examine the dynamics of online deliberation. This is also useful on the policy level. First, it allows decision-makers to test the impacts of different initiatives on deliberation. For example, they can track the discussion networks before and after the initiatives, measure the deliberative potential of discussions over time, and compare the changes from reciprocity, diversity and equality. Second, it reveals the positive impacts of social movements on the deliberative potential of online discussion, which aligns with Ballew et al.'s (2015) statement that environmental activism is a positive function of social media, and can be used as evidence for organisations to initiate more discussions of social movements online.

Chapter 5 and Chapter 6 provide a practical way to analyse the collective framing of climate change by users from different levels. Chapter 5 regards all the users engaged as a whole at a macro level, and Chapter 6 focuses on different user groups and investigates the collective framing of each group at a micro level. Both levels are important for us to explore user-generated content. Other researchers can also take advantage of my categories of user groups to analyse climate change communication online, and even to analyse other political topics.

Climate change communicators can get some evidence from Chapter 5 about how users on Twitter are framing climate change, and design their communication strategies based on that. For example, they can focus more on the efficacy and actions rather than emphasising the consequences of climate change.

Scholars such as Colvin et al. (2019) have called for more evidence for scholars and decision-makers on how the public accepts NE. Chapter 6 is an important study for this purpose, not only presenting the frames but relating the frames to different user groups, even with trends of the evolution. For example, it reveals that users tend to twist the mitigation direction to rely on natural solutions rather than NE, showing users' hesitance to accept NE as a solution to climate change. Stakeholders can learn from this and work more on clarifying the benefits of NE compared to natural solutions. We can also rethink the role of media in communication on Twitter from the finding that media mainly focuses on the role of business rather than talking about the alternative natural solutions or the conflict ideas about NE, but is it a good phenomenon for emerging technologies related to climate change?

As the nature of user-generated content on Twitter is different from the content on mass media, such as newspapers, rather than using the codebooks from other studies that categorise the content on mass media, I categorised the user-generated hashtags related to climate change on Twitter inductively. This provides other researchers with an example, based on which they can build their own codebooks or even use it for training models in supervised machine learning.

Overall, this thesis as a whole provides a way to measure online discussions from different but complementary aspects utilising multiple methods. This shows the possibility of combining quantitative and qualitative, structural and content-based, static and dynamic methods in the same study. The findings in this thesis help us to understand how users are talking about and interacting with others on the topic of climate change from the perspective of deliberation.

7.5 Future work

Future research could build on the limitations and the findings of this study. I discuss nine of these below.

First, in Chapter 4, I only counted the number of unique users in the discussion to measure diversity. Future studies could combine this with other methods to identify user types. By comparing the changes of different types of users in the discussion networks, we can test diversity more comprehensively. What's more, the structural method used in Chapter 4 is a good attempt to answer my research question. But a more comprehensive way can be used to combine text mining and closer text analysis to dig out the political stances and emotions of users, and the arguments embedded in users' tweets. Future studies can also get users engaged by using surveys, interviews or experiments to investigate the effects of online discussions on users' behaviours.

Second, though the findings in this thesis only apply to one particular social media platform, Twitter, some methods can be extended to – or revised first and then applied to – other platforms, such as Reddit, Facebook and YouTube. For example, structural topic modelling can be used to analyse the framing on other social media platforms. Instead of using network analysis to study hashtag co-occurrence networks, we can use it to study word co-occurrence networks on Reddit. But it is worth noting that the discussion networks on Reddit are very different from Twitter. On Reddit, the comment threads can be constructed as tree-like networks instead (see Weninger et al., 2013, for more details). Compared to Twitter, it is also more difficult to identify user groups on Reddit owing to the high anonymity (Gagnon, 2013).

Third, the ERGMs in Chapter 5 are applied on the MST-filtered network owing to the difficulties in applying them to the large network. Future studies can apply the newly developed techniques to solve this limitation. For example, it is possible to use the bootstrapped maximum pseudolikelihood estimation (MPLE) (for details, see Schmid and Desmarais, 2017) to apply ERGMs to the full network. We can also examine the temporal large networks changing over time. For example, Leifeld et al. (2018) provided a way to examine the dynamics of the big network using ERGMs.

Fourth, in Chapter 5, I categorised the hashtags related to climate change and examined two framing processes that were reflected in the hashtag co-occurrence networks. Future studies can take a step further based on my approaches and work on identifying frames embedded in hashtags.

Fifth, future studies can extend the period and track the evolution of the topic over time, which will give us more insights into how the frames of the topic changed by the interaction of different user groups. By extending the period, we can also investigate the impacts of different events on the deliberation of climate change or other political issues.

Sixth, when I started to collect data in 2018, the Twitter academic API was not yet available. Future works can collect data using the Twitter academic API instead of the public API that I used. The academic API has many strengths compared to the public API. For example, the academic API provides more complete and unbiased data and enables researchers to get both historical data and real-time data. In this way, researchers do not have to collect data frequently, as I had to, and it is also more flexible to choose the period that data covers for the study. See https://developer.twitter.com/en/products/twitter-api/academic-research for more details.

Seventh, having been used for various purposes, including infiltrating political discourses to manipulate political discussions during election periods, a social bot is defined as ‘a computer algorithm that automatically produces content and interacts with humans on social media, trying to emulate and possibly alter their behavior’ (Ferrara et al., 2016, p. 96). Many scholars, such as Stella et al. (2018) and Shao et al. (2018), have pointed out that social bots are dangerous for online ecosystems. I did not distinguish social bots from human accounts in this thesis. As my research is to examine all the user-generated content and present how all the users in the dataset interacted with each other and framed climate change, I regard the content that social bots generated as part of the story. However, it is worth noting that, in recently published research, Chen et al. (2021) found that, among the tweets related to climate change collected during the period 7 January 2020 to 27 January 2020, social bots posted a total of 15.4% of tweets. I would not comment on the accuracy of their methods of detecting social bots, but the number does show a high possibility that social bots influence climate change communication on Twitter a lot. Scholars such as Ramalingaiah et al. (2021) and Martini et al. (2021) have also developed methods to detect social bots on Twitter. Future studies can find a well-developed technique to identify social bots and compare the behaviours and content they generated with other users.

Eighth, future studies can look into how the ongoing Coronavirus pandemic has influenced online deliberation in climate change on social media, as the climate-related discussions and movements have been changed significantly. For example, with the enforcement of social distancing, climate activists cancelled in-person protests and moved activism online (Fisher and Nasrin, 2021).

Finally, I manually coded the users in Chapter 6 into different user groups, but this approach is suitable under the conditions that the dataset only covers three months, and NE was not a very popular topic at the time. For a longer period or other more popular topics, researchers can combine my approach with supervised machine learning. For example, they can use the data source for manual coding and the results as labels to train the models for clarification. What’s more, apart from comparing different user groups framing, future works can also study different celebrities’ framing using structural topic modelling. Scholars such as Boykoff and Goodman (2009) have stated the positive impacts of celebrities in raising public awareness and social movements to forcing climate policy changes. It is worthwhile studying how celebrities frame climate change or related technologies online, and how they influence the deliberative potential of the related discussions.

7.6 Conclusion

Despite the limitations discussed above, we can point to a few potential moments where deliberation does occur online. There are many reasons that social media is worrying because of its incomplete capacity to deliver deliberation. Nevertheless, some positivity exists. We can see that there is some potential for an optimistic approach to deliberation online. As Niemeyer (2014) suggested, '[a]lthough deliberative democracy might be difficult to achieve – perhaps even elusive in any ideal sense – there is potential for feedback within the deliberative system where good examples of deliberation contribute to further improvement in deliberative capacity' (p. 38). Ideal deliberation is not assumed in this thesis to be achieved in discussions on social media, but the positive pieces of evidence from this study give us hope and confidence in its deliberative potential. Before solving the problem, we need to know the status of the problem. The clues of how users are framing and interacting with the topic of climate change on Twitter provided in this thesis help us to explore the status of the problem. As it is not limited to the topic of climate change, the methodology can be extended to many other political issues. Empirical research of online deliberation remains in its early stages, and I expect that future studies will considerably refine the measures that I applied herein.

Appendix

Table A-1 Hashtag categories and examples

First-level categories	Definition
Collective action	Bottom-up actions, appeal for action, or social movements for climate change. e.g. #climatestrike, #extinctionrebellion
General climate change	Content about climate change in general. e.g. #climate, #globalwarming
Ecosystems and biodiversity	Living organisms in conjunction with their environment's nonliving components, interacting as a system. e.g. #biodiversity, #wildlife
Politics	Hashtags, including general political hashtags. e.g. #auspol, #brexit
Policy	e.g. #guncontrol, #climatepolicy
Energy supply and use	Energy source, transmission, and storage. e.g. #renewableenergy, #solarpower
Uncertainty	Climate denial or doubting/checking about the facts; counter-uncertainty. e.g. #climatechangehoax, #factsmatter
Science	Hashtags about research and education. e.g. #science, #research
Conference/forum	Hashtags of conferences or forums about climate change. e.g. #cop24, #climateactionsummit
Government/intergovernment initiated plan/action	e.g. #parisagreement, #unfccc
Carbon emissions	Hashtags about carbon emission, excluding energy-related hashtags. e.g. #carbon, #carbonfootprint
Pollution	Hashtags about pollution. e.g. #pollution, #plasticpollution
Celebrity/individual	Hashtags of individuals' names. e.g. #trump, #gretathunberg
Location	Hashtags of locations. e.g. #london, #california
Organisation	Entities comprising people with purposes, such as an institution, or an association. e.g. #cpc, #nasa
Public health	Hashtags about health effects of climate change. e.g. #mentalhealth, #cancer
Technology	Technology-related hashtags, except for energy-related hashtags. e.g. #tech, #cleantech
Food systems	Production, aggregation, processing, distribution, consumption and disposal of food products. e.g. #foodwaste, #nutrition
Weather	Extreme weather and natural disaster. e.g. #drought, #flooding
Media	Media platforms, programs, and resources e.g. #news, #blog
Ideology	e.g. #socialism, #capitalism
Transportation	e.g. #ev, #cars
Other social issues	Security, human rights, etc. e.g. #inequality, #immigration
Scientific certainty	IPCC, UN, or other organisations' reports e.g. #1o5c, #sr15
Economy	Economy, business and finance. e.g. #circulareconomy, #startups
Art	e.g. #design, #art
Community	Groups of people. e.g. #farmers, #indigenous
Cities and the built environment	e.g. #infrastructure, #buildings
Gender	e.g. #women, #gender
Other	Hashtags that cannot be sorted into the above categories. e.g. #retweet, #amwriting

Table A-2 Categories and counts of the top 1000 hashtags

Rank	First-level categories of hashtags	Hashtag counts	Second-level categories of hashtags	Hashtag counts (887,981 in total)
1	Collective action	205007	Efficacy and actions	219300
18	Government/intergovernment initiated plan/action	14293		
4	Ecosystems and biodiversity	77894	Consequences	150681
7	Weather	22892		
15	Economy	12927		
16	Food systems	13411		
19	Pollution	12751		
23	Public health	9709		
5	Energy supply and use	65087	Causes and Solutions	144573
12	Science	14460		
13	Technology	14740		
9	Carbon emissions	22262		
11	Policy	18729		
25	Cities and the built environment	6386		
28	Transportation	4006		
3	Politics	98136	Conflicts	119718
14	Uncertainty	15708		
26	Scientific certainty	5874		
2	General climate change	111669	General climate change	111669
6	Location	47012	Location	47012
10	Conference/forum	18586	Media	41662
8	Media	20337		
30	Art	2739		
17	Celebrity/individual	11880	Actors	30464
20	Organisation	11038		
24	Community	7546		
21	Other social issues	9455	Other social concerns	16241
27	Ideology	3425		
29	Gender	3361		
22	Other	6661	Other	6661

Table A-3 Structural types of hashtags in Period 1

	Hashtag	Second-level categories	Degree rank	Betweenness rank	Degree	Betweenness
Global hub	climate	General climate change	1	7	364	15530
	globalwarming	General climate change	2	4	363	22972
	environment	Consequences	3	1	363	44130.5
	climateaction	Efficacy and actions	4	2	345	39814.5
	sustainability	Efficacy and actions	5	6	271	16050
	science	Causes and solutions	6	12	254	3643.5
	energy	Causes and solutions	7	5	251	21464
	cop24	Media	8	10	231	4561
	auspol	Conflicts	9	3	219	33272.5
	pollution	Consequences	10	17	219	2452
	renewables	Causes and solutions	12	20	212	2160
	parisagreement	Efficacy and actions	13	18	207	2315
	nature	Consequences	14	46	204	892
	actonclimate	Efficacy and actions	15	9	204	8430
	ipcc	Actors	17	32	199	980
	water	Consequences	19	29	186	1382
	cdnpoli	Conflicts	20	8	177	13549.5
	trump	Actors	21	11	177	4127
	sdgs	Efficacy and actions	22	14	173	3179
	cleanenergy	Causes and solutions	23	24	172	1765
	earth	Consequences	24	21	172	1945
	co2	Causes and solutions	25	15	166	3051
	carbon	Causes and solutions	28	42	162	905
	ocean	Consequences	30	22	157	1919
	coal	Causes and solutions	35	34	147	924
	agriculture	Consequences	37	36	147	923
	drought	Consequences	39	31	146	1088
Local hub	fossilfuels	Causes and solutions	26	166	164	0
	green	Conflicts	29	121	157	1
	un	Actors	31	133	156	0
	innovation	Causes and solutions	33	111	148	2
	weather	Consequences	34	122	148	1
	economy	Consequences	36	220	147	0
	future	General climate change	38	170	146	0
	forests	Consequences	41	97	142	8
	environmental	Consequences	42	240	139	0
	news	Media	43	107	138	3
	canada	Location	44	120	138	1
	humanrights	Other social concerns	45	106	133	3
	emissions	Causes and solutions	46	99	132	8
Bridge	animals	Consequences	113	13	83	3606
	vegan	Efficacy and actions	129	23	76	1817
	hurricane	Consequences	108	30	86	1170
	cpc	Actors	397	37	16	922
	art	Media	144	38	72	922
	onpoli	Conflicts	121	40	79	917

hurricaneflorence	Consequences	170	41	63	916
security	Other social concerns	107	44	86	894
women	Other social concerns	101	45	89	894

Table A-4 Structural types of hashtags in Period 2

	Hashtag	Group category	Degree rank	Betweenness rank	Degree	Betweenness
Global hub	climateaction	Efficacy and actions	1	4	468	26041
	climate	General climate change	2	1	460	49463.5
	environment	Consequences	3	2	457	41829.5
	globalwarming	General climate change	4	5	454	25233
	climatecrisis	General climate change	5	8	446	19633
	climateemergency	General climate change	6	9	445	12292
	climatestrike	Efficacy and actions	7	13	405	3699
	sustainability	Efficacy and actions	9	7	398	22723.5
	energy	Causes and solutions	11	10	394	10210
	greennewdeal	Causes and solutions	12	11	392	6237
	actonclimate	Efficacy and actions	15	15	381	2823
	nature	Consequences	16	28	360	1602
	renewableenergy	Causes and solutions	17	19	356	2543
	water	Consequences	18	23	352	2385
	earth	Consequences	19	45	352	995
	co2	Causes and solutions	20	27	346	1607
	health	Consequences	21	31	343	1494
	extinctionrebellion	Efficacy and actions	23	43	338	995
	sdgs	Efficacy and actions	24	14	335	2933
	auspol	Conflicts	28	6	327	22738
	fridaysforfuture	Efficacy and actions	29	16	324	2632
	trump	Actors	30	26	320	1711
	biodiversity	Consequences	32	22	318	2395
	solar	Causes and solutions	34	21	317	2413
	parisagreement	Efficacy and actions	36	42	314	995
	ocean	Consequences	38	20	307	2467
	politics	Conflicts	40	17	305	2580
	cdnpoli	Conflicts	42	3	304	28813
	agriculture	Consequences	44	39	294	1025
	climatejustice	Efficacy and actions	48	37	289	1373
	food	Consequences	50	34	288	1479
Local hub	climatechangeisreal	Conflicts	8	141	402	0
	climateactionnow	Efficacy and actions	14	196	387	0
	emissions	Causes and solutions	27	150	327	0
	environmental	Consequences	31	186	320	0
	green	Conflicts	33	163	318	0
	fossilfuels	Causes and solutions	37	211	314	0
	weather	Consequences	41	255	305	0
	canada	Location	43	180	299	0
	planet	General climate change	46	310	290	0
Bridge	medium	Media	412	12	67	3850.83333
	art	Media	102	24	216	1966
	maga	Conflicts	108	30	212	1500
	vegan	Efficacy and actions	135	32	195	1491
	glacier	Consequences	220	38	145	1278
	writer	Actors	417	40	64	1019

resist	Efficacy and actions	111	41	211	1018
energyefficiency	Causes and solutions	130	46	197	994
buildings	Causes and solutions	259	48	125	985

Table A-5 Frames from topic modelling results

Frame	Topic no.	Top words	Label
General support	1	Highest prob: emissions, negative, zero, net, reducing, enough, says FREX: net, zero, #netzero, reducing, emission, positive, cc Lift: allure, positive, scenarios, nets, 1.5c, achieved, #netzero Score: emissions, negative, allure, zero, net, positive, reducing	Taking action on emissions for net-zero
	3	Highest prob: many, including, please, role, goals, management, drawdown FREX: please, many, deforestation, goals, sustainability, drawdown, exist Lift: encouraging, incorrect, send, weather, exist, please, priority Score: encouraging, many, please, drawdown, goals, incorrect, deforestation	Agreements for land management
	5	Highest prob: #carboncapture, read, #co2, capture, #emissions, ccamerica, utilization FREX: #carboncapture, #emissions, #ccamerica, read, works, ccamerica, #dolphinn2 Lift: #dolphinn2, reuse, #ccstechfacts, #carboncapture, nova, #ccamerica, works Score: reuse, #carboncapture, works, #emissions, #co2, #dolphinn2, ccamerica	Utilising carbon capture technology
	7	Highest prob: make, can, people, see, today, time, money FREX: make, today, money, people, cutting, anyone, see Lift: bold, money, tomorrow, today, excellent, make, side Score: bold, make, people, today, see, money, time	Promise of NE technology
	23	Highest prob: need, capture, know, solution, fight, action, co2 FREX: catching, know, need, action, cbc, solution, gears Lift: gears, catching, iot, ai, cbc, engineer, hype Score: gears, need, catching, know, blowing, fight, cbc	NE as a solution to CC
Uncertainty/doubt	9	Highest prob: co2, technologies, removal, interesting, article, greenhouse, atmospheric FREX: progress, atmospheric, greenhouse, interesting, removal, oceans, technologies Lift: progress, mof, law, atmospheric, oceans, solid, review Score: progress, co2, technologies, removal, comments, review, greenhouse	NE as only part of solution to climate crisis
	10	Highest prob: co2, technologies, removal, interesting, article, greenhouse, atmospheric FREX: progress, atmospheric, greenhouse, interesting, removal, oceans, technologies Lift: progress, mof, law, atmospheric, oceans, solid, review Score: progress, co2, technologies, removal, comments, review, greenhouse	NE as a false solution
	11	Highest prob: good, get, going, stop, want, keep, go FREX: keep, get, right, want, stop, going, good	Moral hazard

		Lift: simple, jail, card, try, keep, multiple, right Score: simple, good, keep, get, going, stop, go	
	20	Highest prob: based, come, lead, strategy, opportunities, risk, report FREX: opportunities, watch, lead, design, risk, approaches, related Lift: johnson, saying, design, watch, recently, related, discussion Score: johnson, watch, based, design, opportunities, discussion, risk	Uncertainty (not very clear)
	21	Highest prob: climate, change, important, mitigation, massive, role, mitigate FREX: mitigation, avoid, tool, change, mitigate, debate, climate Lift: dumber, generator, tool, biden, avoid, mitigation, debate Score: climate, change, dumber, mitigation, avoid, important, mitigate	Importance of NE in climate change mitigation
	29	Highest prob: air, sucking, fix, climate, emergency, magic, simon FREX: fix, magic, emergency, simon, lewis, sucking, air Lift: lewis, magic, simon, emergency, fix, usual, fantasy Score: lewis, emergency, sucking, magic, fix, air, simon	NE is not a magic fix for the climate crisis
	31	Highest prob: cost, much, capture, far, costs, talking, engineering FREX: costs, far, ton, talking, cost, delaney, #demdebate Lift: wow, geo, ton, alternative, #demdebate, tonne, delaney Score: wow, cost, much, delaney, costs, #demdebate, talking	The debate around the financial costs of NE
	38	Highest prob: cent, capture, day, seems, r, #environment FREX: cent, ecosearch, day, web, seems, century Lift: century, proponents, web, ecosearch, cent, op, cell Score: century, cent, day, ecosearch, web, seems	NE as a unviable solution
	39	Highest prob: world, capture, best, times, around, facility, potential FREX: facility, emits, sequestered, world, form, best, facilities Lift: facility, emits, boundary, exempt, device, dam, sequestered Score: emits, world, best, facility, times, sequestered, around	CCS facilitates emissions more than it captures
Natural solutions	2	Highest prob: blue, management, science, store, ecosystems, ocean, coastal FREX: fiber, coastal, mangroves, ecosystems, ocean, blue, black Lift: black, permanently, fiber, coastal, mangroves, terrestrial, mangrove Score: blue, permanently, fiber, case, ecosystems, coastal, black	The role/importance of blue carbon ecosystems

12	Highest prob: new, capture, can, used, study, paper, waste FREX: used, waste, paper, developing, ryan, turn, nearly Lift: capturetech, streams, nearly, ryan, ethanol, developing, waste Score: capturetech, new, used, waste, paper, ryan, developing	Funding for agriculture/natural NE solutions
13	Highest prob: sequestration, forests, forest, water, benefits, land, biodiversity FREX: forest, habitat, ecosystem, services, structurally, forests, biodiversity Lift: structurally, plantations, grasslands, prairie, habitat, forest, services Score: structurally, sequestration, forests, forest, biodiversity, better, habitat	Role of natural NE solutions
24	Highest prob: years, part, every, sequestration, worth, vital, now FREX: part, ppm, burn, every, worth, pathway, years Lift: pathway, ppm, football, friend, jones, part, burn Score: pathway, part, mention, friend, years, ppm, vital	Fragility of natural carbon sinks
25	Highest prob: plants, capture, power, better, carbon, scientists, solar FREX: plants, gene, edit, scientists, wind, better, plastic Lift: #music, edit, gene, #futurism, #newmusic, plants, scientists Score: #music, plants, gene, scientists, better, edit, power	Scientific development of natural solutions
30	Highest prob: trees, tree, planting, year, can, acre, tons FREX: acre, planting, tons, average, absorb, tree, empress Lift: oak, pine, average, acre, absorb, mature, tons Score: average, trees, tree, empress, planting, acre, tons	Improving natural solutions
32	Highest prob: #climatechange, atmosphere, #carbon, dioxide, #climate, nature, remove FREX: #climatechange, remove, #climate, atmosphere, #carbon, #globalwarming, nature Lift: #soils, explained, aimed, mother, remove, removes, #climatechange Score: explained, #carbon, #climatechange, atmosphere, remove, #climate, dioxide	Tapping into natural NE solutions
36	Highest prob: research, environmental, economic, shows, among, issue, nothing FREX: research, education, shows, indigenous, environmental, nothing, grant Lift: australia's'science, education, oscars, winners, eureka, grant, programs Score: australia's'science, research, blue, environmental, indigenous, education, steel	Role of natural NE solutions
37	Highest prob: capture, technology, carbon, efficient, already, world's, might	Role of natural NE solutions

		FREX: technology, efficient, bloomberg, world's, might, already, exists Lift: bloomberg, efficient, technology, exists, world's, might, xom Score: bloomberg, technology, efficient, already, might, world's, capture	
Political support	17	Highest prob: planet, save, last, really, space, hope, earth FREX: planet, hope, mirrors, last, yang, andrew, earth Lift: andrew, mirrors, resort, proposes, planet, hope, yang Score: resort, planet, save, mirrors, last, space, yang	Politician engaged in NE
	19	Highest prob: idea, reduction, actually, neutral, carbon, capture, another FREX: neutral, biofuels, though, sense, visit, reduction, trump Lift: trump, visit, common, biofuels, drop, implementation, sense Score: trump, reduction, idea, actually, neutral, pollution, biofuels	Political support for NE
	22	Highest prob: capture, green, tax, develop, invest, team, billion FREX: develop, green, infrastructure, billion, invest, team, national Lift: ub, awarded, ucla, #demdebates, develop, vehicles, infrastructure Score: ub, green, develop, team, tax, infrastructure, incentives	Government funding for NE technology/generally NE
	34	Highest prob: scale, large, lot, making, capture, likely, industrial FREX: scale, lot, making, likely, large, mean, dac Lift: congr, became, puts, dac, scale, lot, likely Score: puts, scale, large, lot, making, likely, congr	Role of government/government funding
	43	Highest prob: gas, industry, natural, capture, oil, technologies, economy FREX: gas, australian, economy, program, natural, mining, de Lift: advocates, beers, de, australian, transform, continued, minister Score: advocates, gas, industry, recommends, natural, australian, group	Role of government/government funding
Role of business	4	Highest prob: companies, production, development, capture, can, sea, north FREX: sea, north, development, companies, equinor, production, centre Lift: kelp, sea, north, equinor, cooperation, centre, aims Score: kelp, companies, sea, production, equinor, north, development	Role of companies/business
	14	Highest prob: carbon, one, materials, explore, company, turns, soap FREX: soap, turns, calgary, explore, carbon, exxonmobil, micro	Role of companies/business in technology/solutions

		Lift: clarifies, calgary, soap, micro, scope, turns, exxonmobil Score: carbon, clarifies, exxonmobil, soap, mosaic, one, explore	
	15	Highest prob: air, co2, big, oil, back, using, business FREX: back, big, trillion, solve, pulling, dollar, business Lift: pulling, xprize, dollar, energies, solve, trillion, vox Score: pulling, air, dollar, gates, trying, solve, sucking	Role of companies/business in technology/solutions
	16	Highest prob: news, great, investment, something, bad, short, significant FREX: great, investment, footprint, significant, bad, news, thread Lift: explains, failed, great, footprint, terms, thread, short Score: explains, news, great, something, investment, bad, footprint	Role of business (not very clear)
	18	Highest prob: emissions, negative, commitment, stripe's, decrement, stripe, corporate FREX: commitment, stripe's, decrement, corporate, negative, stripe, emissions Lift: decrement, commitment, stripe's, corporate, payment, immediately, purchase Score: decrement, stripe's, negative, commitment, emissions, stripe, hacker	Companies committing to NE/buying NE
	40	Highest prob: plant, work, capture, carbon, million, bill, trees FREX: work, plant, backed, #cleantech, bill, senate, house Lift: backed, gains, senate, #cleantech, house, bills, work Score: gains, gates, backed, bill, plant, million, work	Role of business
	41	Highest prob: plant, work, capture, carbon, million, bill, trees FREX: work, plant, backed, #cleantech, bill, senate, house Lift: backed, gains, senate, #cleantech, house, bills, work Score: gains, gates, backed, bill, plant, million, work	Role of business
Role of fossil fuel industry	27	Highest prob: future, fossil, fuel, fuels, must, burning, capture FREX: fossil, future, yes, must, fuels, fuel, epa Lift: epa, technique, today's, fossil, yes, finally, generations Score: epa, fossil, future, fuel, fuels, technique, must	Doubt about NE solutions as it related to the interest of fossil fuel companies
	28	Highest prob: coal, plan, capture, carbon, industry, power, generation FREX: coal, survival, fired, plan, stakes, juan, early Lift: juan, stakes, survival, fired, coal, sen, san Score: stakes, coal, plan, survival, update, fired, juan	NE solution for survival of fossil fuel companies

	35	Highest prob: energy, global, use, direct, machines, clean, us FREX: quarter, machines, use, global, energy, direct, heating Lift: #kochbrothers, #strikewithus, coverup, dms, foreknowledge, liable, quarter Score: quarter, energy, global, use, machines, direct, coverup	Fossil fuel monopolisation of NE technologies
	42	Highest prob: gas, industry, natural, capture, oil, technologies, economy FREX: gas, australian, economy, program, natural, mining, de Lift: advocates, beers, de, australian, transform, continued, minister Score: advocates, gas, industry, recommends, natural, australian, group	NE solution for survival of fossil fuel companies
Scientific/technological progress	6	Highest prob: capture, tech, carbon, new, funding, million, partnership FREX: expands, partnership, membranes, gen, tech, funding, lanzatech Lift: gen, expands, techcrunch, membranes, performance, partnership, startup Score: gen, expands, lanzatech, partnership, funding, tech, million	Funding/partnerships for NE technological development
	8	Highest prob: co2, technologies, removal, interesting, article, greenhouse, atmospheric FREX: progress, atmospheric, greenhouse, interesting, removal, oceans, technologies Lift: progress, mof, law, atmospheric, oceans, solid, review Score: progress, co2, technologies, removal, comments, review, greenhouse	Importance of developing NE technology
	26	Highest prob: think, means, food, answer, reduce, rather, levels FREX: answer, levels, means, n, think, hemp, cycle Lift: exxonmobil's, metal, tiny, fraction, n, asap, answer Score: exxonmobil's, mofs, captures, answer, think, means, tiny	Scientific advancement in NE technology
	33	Highest prob: soil, sequestration, carbon, agriculture, farmers, farming, health FREX: soil, farmers, soils, regenerative, indigo, agriculture, practices Lift: gevo, probiotics, amplify, indigo, locus, terraton, airborne Score: soil, probiotics, sequestration, farmers, agriculture, regenerative, soils	Scientific advancement in NE technology

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